Report from Dagstuhl Seminar 14081

Robots Learning from Experiences

Edited by

Anthony G. Cohn[1], Bernd Neumann[2], Alessandro Saffiotti[3], and Markus Vincze[4]

1 **University of Leeds, GB,** a.g.cohn@leeds.ac.uk
2 **Universität Hamburg, DE,** neumann@informatik.uni-hamburg.de
3 **University of Örebro, SE,** asaffio@aass.oru.se
4 **TU Wien, AT,** vincze@acin.tuwien.ac.at

Abstract

This report documents the programme and the outcomes of Dagstuhl Seminar 14081 "Robots Learning from Experiences". The report begins with a summary comprising information about the seminar topics, the programme, important discussion points, and conclusions. The main body of the report consists of the abstracts of 25 presentations given at the seminar, and of four reports about discussion groups.

Seminar February 17–21, 2014 – http://www.dagstuhl.de/14081
1998 ACM Subject Classification I.2.6 Concept Learning
Keywords and phrases Learning, experiences, cognitive systems
Digital Object Identifier 10.4230/DagRep.4.2.79

1 Executive Summary

Anthony G. Cohn
Bernd Neumann
Alessandro Saffiotti
Markus Vincze

Topics and Motivation

The ability to exploit experiences is an important asset of intelligent beings. Experiences provide a rich resource for learning, solving problems, avoiding difficulties, predicting the effects of activities, and obtaining commonsense insights. Current robots do not in general possess this ability, and this is a decisive reason for the often perceived "lack of intelligence" of current robotic systems: they repeat mistakes, do not learn to anticipate happenings in their environment, and need detailed instructions for each specific task.

> Consider an everyday task of a service robot, such as grasping a cup from a cupboard and bringing it to a person sitting at a table. This task may occur in many variations and under unpredictable circumstances. For example, persons may sit at different sides of a table, a direct path to the table may be blocked, the table may be cluttered with various objects, hot water may be ready or not, the cup on the shelf may be upside-down, etc. It is clearly infeasible to provide the robot with precise instructions for all contingencies at design time or to specify tasks with highly detailed instructions

for each particular concrete situation which may arise. Hence without such knowledge, robot behaviour is bound to lack robustness if the robot cannot autonomously adapt to new situations.

How would the robot, for example, avoid pouring coffee into an upside-down cup? Based on experiences with multiple pouring actions, the robot will have formed a conceptualisation of all concomitant circumstances of successful pouring, for example to pour into a "container". The robot may not know the name of this conceptualisation but will know that it must be open on top, hollow, empty, etc. Similarly, the robot may have encountered upside-down objects before and hence be able to conceptualise the corrective action of turning an object to make it a usable container.

This seminar has brought together experts and scholars from the robotics, learning, and knowledge representation communities to discuss current approaches to make robots learn from experiences. Emphasis was on the representation of real-world experiences and on exploiting experiences for autonomous acting in a changing or partially unknown environment.

2 Table of Contents

3 Seminar Overview

Programme

The seminar was attended by 41 participants. Based on abstracts submitted before, the organizers had proposed a tentative programme and distributed it to all participants. The programme was slighly adapted during the seminar, its final version is shown below. The talks were presented as shown in the schedule (Fig. 1). Thanks to the speakers, there was sufficient time for discussion after the talks, and the time frame could be kept without difficulties.

The invited participants included delegates from several EU projects that all share a strong focus on the workshop topics (RACE, STRANDS, Co-Friends, RobotHearth, RoboHow, GeRT, XPERIENCE). This choice was aimed at maximizing the sharing of knowledge and results across those projects both through presentations and, more importantly, though informal discussions.

	Monday		Tuesday		Wednesday		Thursday		Friday
08:45	Organizers, all	Opening, short presentations	Luc De Raedt KU Leuven	Statistical Relational Learning for Robotics and Computer Vision	Ivan Bratko Univ. of Ljubljana	Discovery of Abstract Notions by a Robot	Carme Torras UPC – Barcelona	Robot manipulation in human environments: Challenges for learning	Discussion Springer Book
09:15	Bernd Neumann Univ. of Hamburg	Introduction to seminar topic			Krishna Sandeep Reddy Dubba Univ. of Leeds	Scene layout conceptualization and recognition using graphs			
09:45	Coffee								
10:15	Michael Beetz Univ. of Bremen	Experience-based Learning for Bayesian Cognitive Robotics	Michael Zillich TU Wien	Project report STRANDS	Martin Günther Univ. of Osnabrück	Context-aware semantic object mapping for plan execution	Manfred Hild Humboldt University Berlin	Self-Exploration of Autonomous Robots Using Attractor-Based	Reports from discussion groups
10:45			Jianwei Zhang Univ. of Hamburg	Project Report RACE	Vaclav (Vasek) Hlavac Czech TU in Prague	Dual-arm manipulation with clothes, lessons from CloPeMa project.	Sebastian Stock Univ. of Osnabrück	Towards an integrated hierarchical planner for complex robot tasks	
11:15	Pierre-Yves Oudeyer INRIA – Bordeaux	Developmental robotics: lifelong learning and the morphogenesis of developmental structures	Federico Pecora Univ. of Orebro	Reasoning about Learned Knowledge for Robots: the Next Big Challenge for AI?	Laurent Orseau AgroParisTech – Paris	Beyond the traditional agency framework	Sebastian Rockel Univ. of Hamburg	Beyond state-of-the-art Planning: A Survey of Imaginary Planning	
11:45			All	Collecting discussion topics	All	Collecting discussion topics	Muralikrishna Sridhar Univ. of Leeds +	Scene Understanding from Videos	Wrapping up by organizers
12:15	Lunch								
14:00	Luc Steels Free Univ. of Brussels	Robot tutoring	Marek S. Kopicki Univ. of Birmingham	Learning to generalise grasps to novel objects	Excursion, hike		Discussion groups		Departure
14:30	Richard Bowden Univ. of Surrey	Learning by Imitation	Lorenzo Jamone TU Lisboa	Autonomous Online Learning of Sensori-Motor Internal Models in Humanoid Robots					
15:00	Ales Leonardis Univ. of Birmingham	Compositional hierarchies for learning visual representations and building knowledge from experience	Sven Behnke Univ. of Bonn	Manipulation Skill Learning for Cognitive Service Robots					
15:30	Coffee								
16:00	Ralf Möller TU Hamburg-Harburg	Location Prediction Based on Mobility Patterns in Location Histories	Alexandre Bernardino TU Lisboa	Co-Development of Visuo-Motor Structures			Discussion groups		
16:30	Francois Bremont INRIA - Sophia Antipolis	Scene understanding for Activity Monitoring	Jure Zabkar Univ. of Ljubljana	Sensorimotor memory: the representation, learning and inference					
17:00	Luis Seabra Lopes Univ. of Aveiro	Conceptualization of objects and activities for open-ended learning in robotics	Emre Ugur Univ. of Innsbruck	Skill development through affordance-based bootstrapping					
17:30	All	Collecting discussion topics	All	Collecting discussion topics					
18:00	Dinner								

Figure 1 Schedule of the seminar.

Seminar Introduction

At the beginning of the opening session, all participants introduced themselves shortly and indicated which special interests they had in the seminar. Bernd Neumann then introduced to the seminar topic. He first gave some examples of what robots could learn from experiences and then pointed out several open issues which should hopefully be addressed and maybe clarified during the seminar. In particular, he addressed knowledge representation issues regarding formalisms and tools. He also pointed out integration issues arising, for example, from divergent requirements of robotic components regarding a common ontology. Another important issue is modelling, in particular when using the standardized language OWL. As yet, there is no standardized support for compositional hierarchies and constraints, among others.

Discussions

Each day, discussion topics were collected for extended treatment in discussion groups. The topics were clustered, and the following discussion sessions were arranged reflecting the interest of the participants:

Session 1a and 1b
- How to construct a good Ontology?
- Representations bridging the gap between high and low level
- Can we learn anything suitable to be used by higher levels?
- Can we use high-level knowledge to influence the low level?
- Semantic vs. low-level information
- Where/how should uncertainty be dealt with in learning robots?
- Computer Vision in Robotics

Session 2
- Learning strategies
- Domain adaptation, knowledge transfer
- What is the role of affordances in robot learning, control and planning?
- Weakly supervised learning
- Learning over long periods
- One-shot learning vs. statistical learning

Session 3
- Setting up learning experiments
- Collecting datasets, robot tasks, challenges
- Performance metrics for learning in Robotics

Session 4a and 4b
- Should we take a system perspective on the above questions?
- Theoretical framework for learning agents
- Selfmodifying agents, representations vs. processes
- Learning commonsense, metaknowledge

The points of views and prevailing opinions voiced in the discussion sessions were collected by rapporteurs and presented in a plenary session on Friday morning.

Book Publication

Participants discussed whether refereed seminar contributions should be collected for a book or special issue of a journal. The majority showed preference and interest in contributing to a book, for example in the Springer LNCS series. It was agreed that the seminar organizers would explore both possibilities.

Conclusions

The questionnaires distributed by the Dagstuhl organization showed that the participants appreciated the organization of the seminar, the contributions of the speakers and the insights gained in the discussions. Hopefully, the seminar has helped to pave the way for a next generation of cognitive robotic systems.

4 Overview of Talks

4.1 Experience-based Learning for Bayesian Cognitive Robotics

Michael Beetz (Universität Bremen, DE)

Bayesian cognitive robotics is a novel paradigm for the knowledge-enabled control of autonomous robots. The paradigm presumes that one of the most powerful ideas to equip robots with comprehensive reasoning capabilities is the lifelong autonomous learning of joint probability distributions over robot control programs, the behavior they generate and the situation-dependent effects they bring about. Having learned such probability distributions from experience, a robot can make predictions, diagnoses and perform other valuable inference tasks in order to improve its problem-solving performance. In this talk, I will present our ongoing research efforts in investigating the realization and the potential impact of Bayesian cognitive robotics by 1. presenting the design of plans facilitating Bayesian cognitive robotics, 2. explaining how the plans collect experiences in performing human-scale manipulation activities, and 3. showing how robots can learn realistic first-order joint probability distributions over plans, their behavior, and the effects they cause.

4.2 Manipulation Skill Learning for Cognitive Service Robots

Sven Behnke (Universität Bonn, DE)

Service robots need to be equipped with sufficient cognitive abilities to perceive their surroundings and to plan their actions. They also need to learn from experience. At University of Bonn, we developed cognitive service robots that integrate robust mobility, object manipulation and intuitive multimodal interaction with human users [1, 2]. In the talk, I report on the learning of manipulation skills. This is based on robust perception of the manipulated objects by laser scanners and RGB-D sensors. We learn models of object geometry and appearance from moving sensors and track them in real time [3]. By means of deformable registration between models and the current RGB-D view, our robot can generalize manipulation skills to novel object instances [4]. For learning manipulation skills, we developed an interactive approach that combines the advantages of reinforcement and imitation learning in a single coherent framework [5]. This method is used to learn the grasping of objects. Goal-directed representation of motion facilitates segmentation of motion sequences into actions and the transfer of motions to new situations [6]. We extend our approach to action sequences [7] and to action hierarchies in a MAXQ hierarchical reinforcement learning formulation in continuous state spaces using Gaussian Process Regression [8]. We demonstrate the ability to efficiently learn solutions to complex tasks in a box stacking scenario. Finally, I report on recent advanced in semantic mapping using object class segmentation of RGB-D images by random forests and 3D SLAM fusion [9] or discriminative superpixel CRF learning [10].

References

1 J. Stückler, D. Droeschel, K. Gräve, D. Holz, M. Schreiber, A. Topalidou- Kyniazopoulou, M. Schwarz, and S. Behnke: Increasing Flexibility of Mobile Manipulation and Intuitive

Human-Robot Interaction in RoboCup@Home. RoboCup 2013: Robot World Cup XVII, LNCS 8371, pp. 135-146, Springer, 2014.
2 J. Stückler, D. Holz, and S. Behnke: RoboCup@Home: Demonstrating Everyday Manipulation Skills in RoboCup@Home. IEEE Robotics & Automation Magazine. 19(2):34-42, 2012.
3 J. Stückler and S. Behnke: Multi-Resolution Surfel Maps for Efficient Dense 3D Modeling and Tracking. Journal of Visual Communication and Image Representation 25(1):137-147, 2014.
4 J. Stückler and S. Behnke: Efficient Deformable Registration of Multi- Resolution Surfel Maps for Object Manipulation Skill Transfer. Robotics and Automation (ICRA), IEEE Int. Conference on, Hong Kong, 2014.
5 K. Gräve, J. Stückler, and S. Behnke: Improving Imitated Grasping Motions through Interactive Expected Deviation Learning. Humanoid Robots (Humanoids), IEEE-RAS Int. Conference on, Nashville, TN, 2010.
6 K. Gräve and S. Behnke: Incremental Action Recognition and Generalizing Motion Generation based on Goal-Directed Features. Intelligent Robots and Systems (IROS), IEEE/RSJ Int. Conf. on, Vilamoura, Portugal, 2012.
7 K. Gräve and S. Behnke: Learning Sequential Tasks Interactively from Demonstrations and Own Experience. Intelligent Robots and Systems (IROS), IEEE/RSJ International Conference on, Tokyo, Japan, 2013.
8 K. Gräve and S. Behnke: Bayesian Exploration and Interactive Demonstration in Continuous State MAXQ-Learning. Robotics and Automation (ICRA), IEEE International Conference on, Hong Kong, 2014.
9 J. Stückler, B. Waldvogel, H. Schulz, and S. Behnke: Dense Real-Time Mapping of Object-Class Semantics from RGB-D Video. Journal of Real-Time Image Processing, 2014.
10 A. C. Müller and S. Behnke: Learning Depth-Sensitive Conditional Random Fields for Semantic Segmentation of RGB-D Images. Robotics and Automation (ICRA), IEEE International Conference on, Hong Kong, 2014.

4.3 On the Co-development of Visuomotor Structures: How to Create an Artificial Retina.

Alexandre Bernardino (Technical University – Lisboa, PT)

Joint work of Ruesch, Jonas; Ferreira, Ricardo; Bernardino, Alexandre
Main reference J. Ruesch, R. Ferreira, A. Bernardino, "A computational approach on the co-development of artificial visual sensorimotor structures," Adaptive Behavior, 21(6):452–464, December 2013.
URL http://dx.doi.org/10.1177/1059712313492176

Many simple biological systems are able to survive and exhibit advanced behavior with very limited neuronal resources due to very adapted sensorimotor systems to their particular environment. Following the same paradigm, and inspired in some solutions found in biological systems, we are working to provide robots with highly optimized sensorimotor processing systems through the joint optimisation of their different subsystems. Having small low-cost embedded robots operating in the real world with reduced computational resources is a necessary step towards the large- scale deployment of robots to perform distributed tasks and/or operate in barely accessible places to execute tasks otherwise impossible for humans. In this talk we present an approach for co-development of sensori-motor structures based on the minimisation of a prediction error under sparsity inducing criteria. We focus particularly on the visuo-motor system an show how to self-organize the retina morphology and the topology of the motor space (motor-primitives) of an agent that collects experiences (pre- and post-action stimuli) on a certain environment. We show that biologically resembling structures can be developed from realistic natural stimuli with very few initial assumptions.

4.4 Learning by Imitation

Richard Bowden (University of Surrey, GB)

We pose learning by imitation as a weakly supervised learning approach where human action or noisy annotation provides weak supervision to the learning process. Trying to identify consistent visual features that correspond to an action or classification then becomes a data mining process. This talk will briefly outline 2 approaches to learning by example. In the first example we will discuss how pre-attentive vision modelled by low level filter banks can provide regressed control signals and scenario classification for an autonomous vehicle. In the second example we will show how standard datamining tools can be used in an active learning framework to provide image and video classification with equal or superior performance to state-of-the-art batch learning approaches using significantly less data.

4.5 Discovery of Abstract Concepts by a Robot

Ivan Bratko (University of Ljubljana, SI)

Joint work of Bratko, Ivan; Leban, Gregor
Main reference I. Bratko, "Autonomous discovery of abstract concepts by a robot," in Proc. of the 10th Int'l Conf. on Adaptive and Natural Computing Algorithms (ICANNGA'11), LNCS, Vol. 6593, pp. 1–11, Springer, 2011.
URL http://dx.doi.org/10.1007/978-3-642-20282-7_1

How could a robot, on its own, discover abstract notions such as a general concept of a tool? In this talk, I will describe one possible approach to this, and present experiments in autonomous discovery of abstract concepts in a robotic domain. The setting involves an autonomous robot performing tasks in its world, collecting data and learning predictive theories about its world. In particular, we are interested in the robot's inventing new abstract concepts that enable the simplification of the robot's current theory about the world. Such newly introduced concepts, sometimes called insights, improve the robot's hypothesis language and thus make the further learning more effective. Examples of insights are discoveries of concepts like mobility, obstacle, stability, etc. It should be noted that these concepts are not explicitly present in the robot's sensory observations, which makes the use of machine learning techniques more difficult. A particular challenge is to make the robot discover functional roles of objects in solving robot manipulation tasks. In an experiment in robot's learning from its plans to solve concrete tasks, the concept of a tool was discovered. Our approach employs machine learning in logic (Inductive Logic Programming) with predicate invention.

4.6 Scene Understanding for Activity Monitoring

Francois Bremond (INRIA Sophia Antipolis – Méditerranée, FR)

Scene understanding is the process, often real time, of perceiving, analyzing and elaborating an interpretation of a 3D dynamic scene observed through a network of sensors (e.g. video cameras). This process consists mainly in matching signal information coming from sensors observing the scene with models which humans are using to understand the scene. Based on that, scene understanding is both adding and extracting semantic from the sensor data characterizing a scene. This scene can contain a number of physical objects of various types (e.g. people, vehicle) interacting with each others or with their environment (e.g. equipment) more or less structured. The scene can last few instants (e.g. the fall of a person) or few months (e.g. the depression of a person), can be limited to a laboratory slide observed through a microscope or go beyond the size of a city. Sensors include usually cameras (e.g. omni- directional, infrared), but also may include microphones and other sensors (e.g. optical cells, contact sensors, physiological sensors, radars, smoke detectors). Scene understanding is influenced by cognitive vision and it requires at least the melding of three areas: computer vision, cognition and software engineering. Scene understanding can achieve five levels of generic computer vision functionality of detection, localization, tracking, recognition and understanding. But scene understanding systems go beyond the detection of visual features such as corners, edges and moving regions to extract information related to the physical world which is meaningful for human operators. Its requirement is also to achieve more robust, resilient, adaptable computer vision functionalities by endowing them with a cognitive faculty: the ability to learn, adapt, weigh alternative solutions, and develop new strategies for analysis and interpretation. In this talk, we will discuss how scene understanding can be applied to Home Care Monitoring.

4.7 Statistical Relational Learning for Robotics and Vision

Luc De Raedt (KU Leuven, BE)

Agents need to reason and learn about the world before they can select the right actions to perform. The world is inherently relational, that is, there exist multiple objects as well as relationships that hold amongst them and there is often knowledge available about the world that can be taken into account. But traditional approaches to robotics and computer vision have difficulties in handling such relations and background knowledge. However, the new field of statistical relational learning tackles this problem by integrating probabilistic models with expressive logical representations and machine learning. In this talk, I shall introduce statistical relational learning [2, 5] (SRL) through a number of techniques and I shall illustrate their use on a number of applications related to robotics, vision and natural language processing. More specifically, I shall introduce the relational representations that underlie SRL, show how they allow one to deal with structured environments, with a variable number of objects and relations as well as with background knowledge. I shall then continue to show how probabilistic and kernel-based methods can be extended to deal with such relational representations in order to learn and reason about the environment. Covered techniques will include Problog, a probabilistic extension of the logic programming language Prolog [3], and kLog, a language for relational learning with kernel-based methods. These techniques shall then be illustrated on some example problems from computer vision, such as recognizing configurations of houses [1], from activity recognition, where activities of daily life can be recognized from sensory information [6], from playing massive multiplayer online games such as Travian [9], where models can be learned to predict future actions and events, and from robotics, where one can use SRL techniques to track occluded objects and reason about affordances in multi-object manipulation tasks [7, 8].

References

1 Laura Antanas, Martijn van Otterlo, José Oramas Mogrovejo, Tinne Tuytelaars, and Luc De Raedt. There are plenty of places like home: Using relational representations in hierarchies for distance-based image understanding. *Neurocomputing*, 123:75–85, 2014.
2 L. De Raedt, P. Frasconi, K. Kersting, and S. Muggleton, eds.. *Probabilistic Inductive Logic Programming – Theory and Applications*, volume 4911 of *Lecture Notes in Artificial Intelligence*. Springer, 2008.
3 L. De Raedt, A. Kimmig, and H. Toivonen. Problog: A probabilistic Prolog and its application in link discovery. In M. Veloso, ed., *IJCAI*, pp. 2462–2467, 2007.
4 Paolo Frasconi, Fabrizio Costa, Luc De Raedt, and Kurt De Grave. klog: A language for logical and relational learning with kernels. *CoRR*, abs/1205.3981, 2012.
5 L. Getoor and B. Taskar, eds., *An Introduction to Statistical Relational Learning*. MIT Press, 2007.
6 Niels Landwehr, Bernd Gutmann, Ingo Thon, Luc De Raedt, and Matthai Philipose. Relational transformation-based tagging for activity recognition. *Fundam. Inform.*, 89(1):111–129, 2008.
7 Bogdan Moldovan, Plinio Moreno, Martijn van Otterlo, José Santos-Victor, and Luc De Raedt. Learning relational affordance models for robots in multi-object manipulation tasks. In *IEEE Int'l Conf. on Robotics and Automation, ICRA 2012*, pp. 4373–4378, 2012.
8 Davide Nitti, Tinne De Laet, and Luc De Raedt. A particle filter for hybrid relational domains. In *2013 IEEE/RSJ Int'l Conf. on Intelligent Robots and Systems, Tokyo, Japan*, pp. 2764–2771, 2013.
9 Ingo Thon, Niels Landwehr, and Luc De Raedt. A simple model for sequences of relational state descriptions. In W. Daelemans, B. Goethals, and K. Morik, eds., *ECML*, volume 5211 of *LNCS*, pp. 506–521. Springer, 2008.

4.8 Conceptualizing Static and Dynamic Scenes

Krishna Sandeep Reddy Dubba (University of Leeds, GB)

Joint work of Dubba, Krishna Sandeep Reddy; de Oliveira, Miguel; Lim,Gi Hyun; Kasaei, Hamidreza; Lopes, Luis Seabra; Tome, Ana; Cohn, Anthony G.; Hogg, David
Main reference K. S. R. Dubba, M. de Oliveira, G. Lim, L. Lopes, A. G. Cohn, D. Hogg, "Grounding Language in Perception for Scene Conceptualization in Autonomous Robots," In Proc. of the AAAI Spring Symposium Series 2014, to appear.
URL http://www.comp.leeds.ac.uk/scsksrd/QRR_AAAI.pdf

In order to behave autonomously, it is desirable for robots to have the ability to use human supervision and learn from different input sources (perception, gestures, verbal and textual descriptions etc). In many machine learning tasks, the supervision is directed specifically towards machines and hence is straight forward clearly annotated examples. But this is not always very practical and recently it was found that the most preferred interface to robots is natural language. Also the supervision might only be available in a rather indirect form, which may be vague and incomplete. This is frequently the case when humans teach other humans since they may assume a particular context and existing world knowledge. We explore this idea here in the setting of conceptualizing objects, scene layouts and environment activities. Initially the robot undergoes training from a human in recognizing some objects in the world and armed with this acquired knowledge it sets out in the world to explore and learn more higher level concepts like static scene layouts and environment activities. Here it has to exploit its learned knowledge and ground language into perception to use inputs from different sources that might have overlapping as well as novel information. When exploring, we assume that the robot is given visual input, without explicit type labels for objects, and also that it has access to more or less generic linguistic descriptions of scene layout. Thus our task here is to learn the spatial structure of a scene layout and simultaneously visual object models it was not trained on. In this work [1], we present a cognitive architecture and learning framework for robot learning through natural human supervision and using multiple input sources by grounding language in perception.

References

1 Krishna S.R. Dubba, Miguel R. de Oliveira, Gi Hyun Lim, Hamidreza Kasaei, Luis Seabra Lopes, Ana Tome and Anthony G. Cohn. *Grounding Language in Perception for Scene Conceptualization in Autonomous Robots.* AAAI Spring Symposium Series, 2014.

4.9 Context-aware Semantic Object Mapping for Plan Execution

Martin Guenther (Universität Osnabrück, DE)

Joint work of Guenther, Martin; Ruiz-Sarmiento, José Raúl; Stock, Sebastian; Hertzberg, Joachim

A service robot that creates and executes plans involving objects in its environment needs a semantic map of those objects and places. Such a map needs to be continually updated with new object recognition results, which may be noisy and incomplete. A key idea of this talk is that the basic object recognition results can be improved by exploiting the rich context between the objects. For example, once a monitor has been detected, the probability of an elongated object in front of it being a keyboard increases. We model these context relations as a Conditional Random Field.

We also present first steps towards a more active semantic perception system: Given a partially recognized scene, ontological knowledge about spatial layouts can be used to hypothesize areas where undetected task-relevant objects are expected. By querying the CRF for the most likely locations of undetected objects, we can plan actions to observe these areas by moving the robot to a different position or by moving occluding objects.

References

1 A. Anand, H. S. Koppula, T. Joachims, and A. Saxena, "Contextually guided semantic labeling and search for three-dimensional point clouds," *Int. J. Rob. Res.*, vol. 32, no. 1, pp. 19–34, 2013.
2 N. Blodow, L. C. Goron, Z.-C. Marton, D. Pangercic, T. Rühr, M. Tenorth, and M. Beetz, "Autonomous semantic mapping for robots performing everyday manipulation tasks in kit-

chen environments," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2011, pp. 4263–4270.
3 N. Blodow, D. Jain, Z.-C. Marton, and M. Beetz, "Perception and probabilistic anchoring for dynamic world state logging," in *Humanoids*. IEEE, 2010, pp. 160–166.
4 M. Gupta, T. Rühr, M. Beetz, and G. S. Sukhatme, "Interactive environment exploration in clutter," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2013, pp. 5265–5272.
5 L. P. Kaelbling and T. Lozano-Pérez, "Integrated task and motion planning in belief space," *I. J. Robotic Res.*, vol. 32, no. 9-10, pp. 1194–1227, 2013.
6 B. Neumann and R. Möller, "On scene interpretation with description logics," *Image Vision Comput.*, vol. 26, no. 1, pp. 82–101, 2008.
7 J. R. Ruiz-Sarmiento, C. Galindo, and J. Gonzalez-Jimenez, "Mobile robot object recognition through the synergy of probabilistic graphical models and semantic knowledge," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Chicago, Illinois, November 2014, (submitted).

4.10 Developmental Learning of Sensori-Motor Internal Models in Humanoid Robots

Lorenzo Jamone (Technical University – Lisboa, PT)

Joint work of Jamone, Lorenzo; Brandao, Martim; Natale, Lorenzo; Hashimoto, Kenji; Sandini, Giulio; Takanishi, Atsuo; Endo, Nobustuna; Metta, Giorgio; Nori, Francesco; Damas, Bruno; Santos-Victor, José
Main reference L. Jamone, M. Brandao, L. Natale, K. Hashimoto, G. Sandini, A. Takanishi, "Autonomous online generation of a motor representation of the workspace for intelligent whole-body reaching," Robotic and Autonomous Systems, 64(4):556–567, April 2014.
URL http://dx.doi.org/10.1016/j.robot.2013.12.011

The future of humanoid robots is to become efficient helpers for humans, both in the execution of everyday tasks and in the accomplishment of tedious and dangerous works. Driven by this vision, researchers have been challenged to design more and more complex robots, that show an increasing number of degrees of freedom and sensors [1, 2]; these robots should be able to cope with the unstructured environment in which humans daily live and act. In particular, it would be desirable that robot behaviors become autonomous (not requiring the supervision of a human expert) and flexible (applicable to different situations and contexts). However, as robots become more complex, building the analytical models needed for robot control is turning more and more difficult and time-consuming. Moreover, the lack of knowledge of certain hard to measure physical parameters and the existence of highly non-linear physical interactions, makes it infeasible to obtain adequate and accurate models for such kind of systems [3]; as a consequence, resorting to modern machine learning techniques is becoming a more and more popular way to provide these complex robots with the necessary representation capability (see [4] for a recent survey). I will present some of the results I obtained during the last five years in providing humanoid robots with the ability to learn sensori-motor internal models (to achieve different motor skills) i) autonomously and ii) incrementally during the goal-directed exploration of the environment. The approach I have been following focuses on some distinctive aspects:

- life-long continuous learning (accounting for both gradual and abrupt modifications in the system);

- goal-directed exploration of the environment (i.e. learning a general model by trying to accomplish specific tasks);
- developmental framework (the acquisition of a motor skill may allow to gather data to learn a new motor skill);
- bio-inspired (human-inspired) learning and control strategies.

I will discuss why goal-directed exploration is beneficial [5], and how suggestions from biology can help to build better robotic systems. I will sketch a developmental path in which a robot starts from basic visual perception to finally achieve goal-directed visually-guided locomotion and intelligent whole- body reaching capabilities, including the ability to reach with tools. Namely, first the robot learns how to the control the neck [6] and eyes to fixate targets in the environment, then it starts learning arm reaching [7] (also using different tools [9]), then it builds incrementally a representation of its own reachable space [8], and finally it exploits this knowledge to perform whole-body reaching [10] and goal-directed walking [11], that are seen as ways to maximize the reachability of visually detected objects. Results obtained on different humanoid robots (namely, James [12], Kobian [2] and iCub [1]) will be presented.

References

1. G. Metta, G. Sandini, D. Vernon, L. Natale, F. Nori, The iCub humanoid robot: an open platform for research in embodied cognition. Workshop on Performance Metrics for Intelligent Systems (2008).
2. N. Endo, A. Takanishi, Development of Whole-body Emotional Expression Humanoid Robot for ADL-assistive RT services. Journal of Robotics and Mechatronics 23, 6, pp. 969–977 (2011).
3. J. Peters, S. Schaal, Learning Operational Space Control. Robotics: Science and Systems (2006).
4. O. Sigaud, C. Salan, V. Padois, On-line regression algorithms for learning mechanical models of robots: A survey. Robotics and Autonomous Systems 59, 12, pp. 1115–1129 (2011).
5. L. Jamone, L. Natale, K. Hashimoto, G. Sandini, A. Takanishi, Learning task space control through goal directed exploration. Int'l Conference on Robotics and Biomimetics (2011).
6. L. Jamone, L. Natale, M. Fumagalli, F. Nori, G. Metta, G. Sandini, Machine- Learning Based Control of a Human-like Tendon Driven Neck. International Conference on Robotics and Automation (2010).
7. L. Jamone, L. Natale, G. Metta, F. Nori, G. Sandini, Autonomous online learning of reaching behavior in a humanoid robot. International Journal of Humanoid Robotics 9, 3, pp. 1250017.1-1250017.26 (2012).
8. L. Jamone, L. Natale, G. Sandini, A. Takanishi, Interactive online learning of the kinematic workspace of a humanoid robot. Int'l Conference on Intelligent Robots and Systems (2012).
9. L. Jamone, B. Damas, N. Endo, J. Santos-Victor, A. Takanishi, Incremental development of multiple tool models for robotic reaching through autonomous exploration. PALADYN Journal of Behavioral Robotics, Vol. 3, No. 3, pp. 113- 127 (2013).
10. L. Jamone, M. Brandao, L. Natale, K. Hashimoto, G. Sandini, A. Takanishi, Autonomous online generation of a motor representation of the workspace for intelligent whole-body reaching. Robotic and Autonomous Systems, Vol. 64, No. 4, pp. 556–567 (2014).
11. M. Brandao, L. Jamone, P. Kryczka, N. Endo, K. Hashimoto, A. Takanishi, Reaching for the unreachable: integration of locomotion and whole-body movements for extended visually guided reaching. International Conference on Humanoid Robots (2013).
12. L. Jamone, G. Metta, F. Nori, G. Sandini, James: A Humanoid Robot Acting over an Unstructured World. International Conference on Humanoid Robots (2006).

4.11 Learning to Generalise Grasps to Novel Objects.

Marek S. Kopicki (University of Birmingham, GB)

Joint work of Kopicki. M.; Detry R.; Schmidt F.; Borst C.; Stolkin R.; Wyatt J.L.
Main reference M. Kopicki., R. Detry, F. Schmidt, C. Borst, R. Stolkin, and J. L. Wyatt, "Learning Dexterous Grasps That Generalise To Novel Objects By Combining Hand And Contact Models," in Proc. of the 2014 IEEE Int'l Conf. on Robotics and Automation (ICRA'14), to appear.

Generalising grasps to novel objects is an open problem in robotics. In this talk I will present a method that can learn grasps for high degree of freedom robots that generalise to novel objects, given as little as one demonstrated grasp. The method is potentially more general and can be used not only in grasping, but also in any kind of robotic applications that involve robot body-environment/object spatial relations. The example could be dexterous manipulation, manipulation of deformable objects, walking robots, etc. During grasp learning two types of probability density are learned that model the demonstrated grasp. The first density type (the contact model) models the relationship of an individual robot link to a local object feature at its neighbourhood. The second density type (the robot configuration model) models the whole robot configuration which is preferable for a particular grasp type. When presented with a new object, many candidate grasps are generated, and a grasp is selected that maximises the product of these densities. The experimental results show successful grasp transfers to novel objects performed on two different robots with different multi-finger hands. The experiments include cases where the robot has only partial information about the object shape and other physical properties.

4.12 Compositional Hierarchies for Learning Visual Representations and for Building Knowledge from Experiences

Ales Leonardis (University of Birmingham, GB)

Building knowledge from experiences is one of the most important capabilities of intelligent artificial systems. This requires proper structures and mechanisms that enable efficient learning, retrieval, and, when necessary, modification and augmentation of the acquired knowledge. Recently, it has become increasingly clear that new approaches are needed to tackle these problems and there have been several indications that possible solutions should be sought in the framework of hierarchical architectures. Among various design choices related to hierarchies, compositional hierarchies show a great promise in terms of scalability, real-time performance, efficient structured on-line learning, shareability, and knowledge transfer. In my talk I will first present our work on compositional hierarchies for learning visual representations and then present some ideas towards generalizing the proposed approach to other modalities and to building knowledge from experiences.

4.13 Location Prediction Based on Mobility Patterns in Location Histories

Ralf Moeller (TU Hamburg-Harburg, DE)

Main reference J. Lüthke, "Location Prediction Based on Mobility Patterns in Location Histories," Master's theis, Hamburg University of Technology, September 2013.
URL http://www.sts.tuhh.de/pw-and-m-theses/2013/luethke13.pdf

Human individuals generally tend to follow several habits during the course of the day. This fact intuitively allows predicting human behavior to a certain degree based on previous observations. A generic algorithm for dynamic location prediction that uses kernel density estimation and quadratic optimization is devleoped and analysed in this presentation. The algorithm was implemented and tested in a large scale environment using mobility traces of taxis. The test results clearly indicate that the algorithm can extract and exploit patterns in the data to predict future locations. For instance, the algorithm achieves an accuracy better than 1000m in approximately 32% of the executed tests using a prediction interval of six minutes. Moreover, in 13% of these tests the prediction error is smaller than 500m. In addition, the test results show that the algorithm is able to estimate the reliability of its predictions with an accuracy of up to 98.75%. As expected, the test results also clearly demonstrate that the prediction capability of the algorithm strongly depends on the properties of the given location data and the underlying stochastic process. We conjecture that the kind of location prediction we present can be adapted to be applicable also in the small scale, i.e., in cases where robots have to directly interact with humans, e.g., for carrying out service tasks.

4.14 Beyond the Traditional Agency Framework

Laurent Orseau (AgroParisTech – Paris, FR)

Joint work of Orseau, Laurent; Ring, Mark
Main reference L. Orseau, M. Ring, "Space-Time Embedded Intelligence. Artificial General Intelligence," in Proc. of the 5th Int'l Conf. on Artificial General Intelligence (AGI'12), LNCS, Vol. 7716, pp. 209–218, Springer, 2012.
URL http://dx.doi.org/10.1007/978-3-642-35506-6_22

In the traditional theoretical framework for dealing with agents, as used in Reinforcement Learning for example, an agent and an environment are put in interaction, but they are considered to be two completely separate entities. In particular, this implies that the computer of the agent is "immortal", along with its source code and memory. Although this is convenient for most purposes, this framework is actually inaccurate and can lead to wrong decisions from an autonomous and intelligent agent. We build several frameworks in order to study some consequences of making the agent being a part of the environment, where the latter can modify directly either the memory or the source code of the former. We conclude by proposing what we call the Space-Time Embedded framework, where the agent can not only be modified by the environment but is also computed by it, and we give a definition of intelligence in this framework.

References

1 Laurent Orseau and Mark Ring. *Self-Modification and Mortality in Artificial Agents*. Artificial General Intelligence, Lecture Notes in Computer Science 6830, pp. 1–10, 2011, doi: 10.1007/978-3-642-22887-2-1.
2 Mark Ring and Laurent Orseau. *Delusion, Survival, and Intelligent Agents*. Artificial General Intelligence, Lecture Notes in Computer Science 6830, pp. 11–20, 2011, doi: 10.1007/978-3-642-22887-2-2.
3 Laurent Orseau and Mark Ring. *Space-Time Embedded Intelligence*. Artificial General Intelligence, Lecture Notes in Computer Science 7716, pp. 209–218, 2012, doi: 10.1007/978-3-642-35506-6-22.
4 Laurent Orseau and Mark Ring. *Memory Issues of Intelligent Agents*. Artificial General Intelligence, Lecture Notes in Computer Science 7716, pp. 219–231, 2012, doi: 10.1007/978-3-642-35506-6-23.

4.15 Developmental Robotics: Lifelong Learning and the Morphogenesis of Developmental Structures

Pierre-Yves Oudeyer (INRIA – Bordeaux, FR)

Joint work of Oudeyer, Pierre-Yves; Kaplan, Frédéric; Baranes, Adrien; Hafner, V.; Nguyen, Mai; Stulp, Freek; Gottlieb, J.; Lopes, Manuel
Main reference P.-Y. Oudeyer, A. Baranes, F. Kaplan, "Intrinsically Motivated Learning of Real World Sensorimotor Skills with Developmental Constraints," in G. Baldassarre, M. Mirolli, eds., Intrinsically Motivated Learning in Natural and Artificial Systems, Springer, 2013; authors' pre-print available at HAL (hal-00788611).
URL http://dx.doi.org/10.1007/978-3-642-32375-1_13
URL http://hal.inria.fr/hal-00788611

Developmental robotics studies and experiments mechanisms for autonomous life-long learning of skills in robots and humans. One of the crucial challenges is due to the sharp contrast between the high-dimensionality of their sensorimotor space and the limited number of physical experiments they can make within their life-time. This also includes the capability to adapt skills to changing environments or to novel tasks. To achieve efficient life-long learning in such complex spaces, humans benefit from various interacting developmental mechanisms which generally structure exploration from simple learning situations to more complex ones. I will present recent research in developmental robotics that has studied several ways to transpose these developmental learning mechanisms to robots. In particular, I will present and discuss computational mechanisms of intrinsically motivated active learning, which automatically select training examples [4, 5], or tasks through goal babbling [2], of increasing complexity, and their interaction with imitation learning [3]„ as well as maturation and body growth where the number of sensori and motor degrees-of-freedom evolve through phases of freezing and freeing [1, 6]. I will discuss them both from the point of view of modeling sensorimotor and cognitive development in infants and from the point of view of technology, i.e. how to build robots capable to learn efficiently in high-dimensional sensorimotor spaces.

References

1 Baranes A., Oudeyer P.-Y. (2011) The interaction of maturational constraints and intrinsic motivations in active motor development, in Proceedings of ICDL-EpiRob 2011.

2 Baranes, A., Oudeyer, P.-Y. (2013) Active Learning of Inverse Models with Intrinsically Motivated Goal Exploration in Robots, Robotics and Autonomous Systems, 61(1), pp. 49–73. doi: 10.1016/j.robot.2012.05.008.
3 Nguyen M., Baranes A. and P.-Y. Oudeyer (2011) Bootstrapping intrinsically motivated learning with human demonstrations, in Proceedings of the IEEE International Conference on Development and Learning, Frankfurt, Germany.
4 Oudeyer P.-Y. Kaplan F. and V. Hafner (2007) Intrinsic motivation systems for autonomous mental development, IEEE Transactions on Evolutionary Computation, 11(2), pp. 265–286.
5 Schmidhuber, J. (1991) Curious model-building control systems, in: Proc. Int. Joint Conf. Neural Netw., volume 2, pp. 1458–1463.
6 Stulp F., Oudeyer P.-Y. (2012) Emergent Proximo-Distal Maturation with Adaptive Exploration, in Proceedings of IEEE International Conference on Development and Learning and Epigenetic Robotics (ICDL-Epirob), San Diego, USA.

4.16 Reasoning about Learned Knowledge for Robots: the Next Big Challenge for AI?

Federico Pecora (University of Örebro, SE)

Joint work of Pecora, Federico; Konecny, Stefan; Mansouri, Masoumeh; Saffiotti, Alessandro
URL http://www.project-race.eu

The robot of the future will possess a great deal of general and domain-specific knowledge, it will be capable of representing in symbolic terms its perceptions, and it will most likely learn much of its knowledge from experience. In order to be competent, this robot must leverage the diverse knowledge it possesses through reasoning. Crucially, the robot's knowledge will not be expressed in one knowledge representation formalism, rather with a multitude of inter-dependent representations, each expressing a subset of aspects (e.g., temporal, causal, resource, taxonomic, common-sense) pertaining to the robot's capabilities, tasks and environment. This poses an important problem: although we may soon have very knowledgeable robots, all we can give them is the ability to reason within particular fragments of their knowledge. The multitude of AI reasoning algorithms that would be necessary in a realistic scenario are studied only individually, and very limited results exist in how to concurrently reason about diverse types of knowledge with current AI techniques.

This talk outlines some of the challenges in hybrid reasoning, with a particular emphasis on robot reasoning tasks. These include planning (reasoning about causal relations), temporal reasoning, symbolic and geometric spatial reasoning, scheduling (reasoning about time and resources), and ontological reasoning. The talk will outline solutions studied in the EU-FP7 RACE project. Focus will be given to a general method for hybrid reasoning grounded on the notion of meta-constraints.

4.17 Predicting Robot Action Results Physically Correct: Towards Imaginary Planning

Sebastian Rockel (Universität Hamburg, DE)

Joint work of Rockel, Sebastian; Klimentjew, Denis; Zhang, Liwei; Zhang Jianwei

Imagination enables humans to consult rules or principles but do not merely apply that rule. Instead humans imagine what the consequences might be of following or not following the rule. It is even commonly maintained that humans constantly do imaginative projection. Furthermore some works conclude that imagination is essential to human reasoning. Our approach is inspired by the concept of imagination and its goal is to employ it on a mobile robot system. The presented work uses physics-based simulation in order to predict action results. Based on robot imagination this talk shall stress supporting scenarios where simulation as the tool for common sense reasoning can be exploited. Different scenarios will be presented that demonstrate an improved performance of such an imaginary planning-based robot system compared to state-of-the-art symbolic planning approaches. A comparison between the presented techniques and a possible integration shall conclude the talk.

References

1 Sebastian Rockel, Denis Klimentjew, Liwei Zhang, Jianwei Zhang. *An Hyperreality Imagination based Reasoning and Evaluation System (HIRES)*, 2014 IEEE International conference on Robotics and Automation (ICRA 2014), Hong Kong (China), 2014. (Accepted)

2 Lasse Einig, Denis Klimentjew, Sebastian Rockel, Jianwei Zhang. *Parallel Plan Execution and Re-planning on a Mobile Robot using State Machines with HTN Planning Systems*, IEEE International Conference on Robotics and Biomimetics (ROBIO), December 2013, Shenzhen (China).

3 S. Rockel, B. Neumann, J. Zhang, K. S. R. Dubba, A. G. Cohn, S. Konecny, M. Mansouri, F. Pecora, A. Saffiotti, M. Günther, S. Stock, J. Hertzberg, A. M. Tome, A. J. Pinho, L. S. Lopes, S. v. Riegen and L. Hotz. *An Ontology-based Multi-level Robot Architecture for Learning from Experiences*. In: Proc. Designing Intelligent Robots: Reintegrating AI II, AAAI Spring Symposium, March 25–27, Stanford (USA), 2013.

4 D. Klimentjew, S. Rockel, J. Zhang. *Towards Scene Analysis based on Multi-Sensor Fusion, Active Perception and Mixed Reality in Mobile Robotics*, In Proceedings of the IEEE First International Conference on Cognitive Systems and Information Processing (CSIP2012), 15–17 December, Beijing (China), 2012.

5 L. Kunze, M. E. Dolha, and M. Beetz. *Logic programming with simulation-based temporal projection for everyday robot object manipulation*, in 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), San Francisco, CA, USA, September, 25–30, 2011.

6 E. Weitnauer, R. Haschke, and H. Ritter. *Evaluating a physics engine as an ingredient for physical reasoning*, in Simulation, Modeling, and Programming for Autonomous Robots, ser. Lecture Notes in Computer Science, N. Ando, S. Balakirsky, T. Hemker, M. Reggiani, and O. Stryk, Eds. Springer Berlin Heidelberg, 2010, vol. 6472, pp. 144–155.

7 A. Boeing and T. Bräunl. *Evaluation of real-time physics simulation systems*, in Proceedings of the 5th International Conference on Computer Graphics and Interactive Techniques in Australia and Southeast Asia, ser. GRAPHITE 07. New York, NY, USA: ACM, 2007, pp. 281–288.

8 B. J. Loasby. *Cognition, imagination and institutions in demand creation*, Journal of Evolutionary Economics, vol. 11, pp. 7–21, 2001.

4.18 Interactive Open-Ended Learning about Objects and Activities

Luis Seabra Lopes (University of Aveiro, PT)

Joint work of Seabra Lopes, Luis; Chauhan, Aneesh, Oliveira, Miguel; Kasaei, S. Hamidreza; Mokhtari, Vahid; Tomé, Ana Maria

We presented an overview of previous work on open-ended learning in robotics, with emphasis on projects in which our group is/was involved [2, 5]. Key characteristics of intelligent service robots as well as some of the issues in the development of such robots were identified [1]. The presentation then focussed on two important phases in experience-based learning, namely experience extraction and experience conceptualization. These two learning steps are addressed in two different domains, namely object category learning [4] and activity schema learning [3]. The human user, playing the role of instructor, helps to speed up and focus the learning process. Aspects of evaluation of open-ended learning were also addressed.

References

1 L. Seabra Lopes and J.H. Connell, Semisentient Robots: Routes to Integrated Intelligence, *IEEE Intelligent Systems*, 16 (5), Computer Society, pp. 10–14, 2001.
2 L. Seabra Lopes and A. Chauhan, How many Words can my Robot learn? An Approach and Experiments with One-Class Learning, *Interaction Studies*, 8 (1), pp. 53–81, 2007.
3 L. Seabra Lopes, Failure Recovery Planning for Robotized Assembly based on Learned Semantic Structures, *IFAC Workshop on Intelligent Assembly and Disassembly (IAD 07)*, Alicante, Spain, pp. 65–70, 2007.
4 L. Seabra Lopes and A. Chauhan, Open-Ended Category Learning for Language Acquisition, *Connection Science*, Taylor & Francis, 20 (4), 277–297, 2008.
5 L. Seabra Lopes and A. Chauhan, Using Spoken Words to guide Open-ended Category Formation, *Cognitive Processing*, Springer, 12 (4), 341–354, 2011.

4.19 Robot Tutoring

Luc Steels (Free University of Brussels, BE)

A lot of research has gone into mechanisms by which a robot could learn from experience. Usually the robot is seen as an agent that receives a corpus of data (ideally sensory states with motor states and possibly effects in the world) and performs some kind of induction to learn when certain actions are appropriate or how actions carried out by others should be interpreted. This approach certainly has to be part of the road towards learning robots. However, in the case of human learning, particularly of symbolic intelligence including language, a tutor (for example a caregiver) plays a crucial role. Learning thus becomes much more interactive. The tutor creates constrained contexts for learning, provides critical feedback, and interprets behaviors by guessing their intend and thus infuses meaning in them. For example, pointing gestures are acquired from attempts to grasp objects out of reach. The caregiver interprets failed grasping and brings the object within reach, from where the grasping gesture itself evolves to become symbolic and the basis of language games. I will argue in this talk that there is great value in studying the coupling between learning and tutoring by setting up experiments in which robots are programmed to act both as learners 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

Sebastian Stock (Universität Osnabrück, DE)

Joint work of Stock, Sebastian; Günther, Martin; Hertzberg, Joachim

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.

References

1 S. Konecny, S. Stock, F. Pecora, A. Saffiotti, "Planning Domain+ Execution Semantics: a Way Towards Robust Execution?," *AAAI Spring Symposium Series: Qualitative Representations for Robots*, 2014.
2 L.P. Kaelbling, T. Lozano-Perez, "Hierarchical task and motion planning in the now," *IEEE International Conference on Robotics and Automation (ICRA)*, 2011.

4.21 Robot Manipulation in Human Environments: Challenges for Learning Algorithms

Carme Torras (UPC – Barcelona, ES)

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.

References

1 Kemp C.C., Edsinger A. and Torres-Jara E. (2007): Challenges for robot manipulation in human environments. IEEE Robotics and Automation Magazine, 14(1): 20–29. doi: 10.1109/MRA.2007.339604

2 Agostini A., Torras C. and Wörgötter F. (2011): Integrating task planning and interactive learning for robots to work in human environments, Int'l Joint Conf. on Artificial Intelligence (IJCAI 11), Barcelona, pp. 2386–2391. http://ijcai.org/papers11/Papers/IJCAI11-398.pdf

3 Rozo L., Calinon S., Caldwell D., Jimenez P. and Torras C. (2013): Learning collaborative impedance-based robot behaviors. 27th Int'l Conf. of the Assoc. for the Advancement of Artificial Intelligence (AAAI-13), Bellevue, Washington, pp. 1422–1428. http://www.aaai.org/ocs/index.php/AAAI/AAAI13/paper/view/6243/6845

4 Colome A., Alenya G. and Torras C. (2013): Handling high parameter dimensionality in reinforcement learning with dynamic motor primitives. ICRA Workshop on "Novel Methods for Learning and Optimization of Control Policies and Trajectories for Robotics", Karlsruhe, Germany. http://www.ias.tu-darmstadt.de/uploads/Research/ICRA2013/Colome.pdf

5 Colome A., Pardo D., Alenya G. and Torras C. (2013): External force estimation during compliant robot manipulation. IEEE Int'l Conf. on Robotics and Automation (ICRA 13), Karlsruhe, Germany, pp. 3535–3540. http://dx.doi.org/10.1109/ICRA.2013.6631072

6 Rozo L., Jimenez P. and Torras C. (2013): A robot learning from demonstration framework to perform force-based manipulation tasks. Intelligent Service Robotics, 6(1): 33–51. doi: 10.1007/s11370-012-0128-9

7 Alenya G., Dellen B. and Torras C. (2011): 3D modelling of leaves from color and ToF data for robotized plant measuring. IEEE Int'l Conf. on Robotics and Automation (ICRA 11), Shanghai, pp. 3408–3414. doi: 10.1109/ICRA 2011.5980092

8 Alenya G., Dellen B., Foix S. and Torras C. (2013): Robotized plant probing: Leaf segmentation utilizing time-of-flight data. IEEE Robotics and Automation Magazine, 20(3): 50–59. doi: 10.1109/MRA.2012.2230118

9 Ramisa A., Alenya G., Moreno-Noguer F. and Torras C. (2012): Using depth and appearance features for informed robot grasping of highly wrinkled clothes. IEEE Int'l Conf. on Robotics and Automation (ICRA 12), St. Paul, Minnesota, pp. 1703–1708. doi: 10.1109/ICRA.2012.6225045

10 Ramisa A., Alenya G., Moreno-Noguer F. and Torras C. (2013): FINDDD: A fast 3D descriptor to characterize textiles for robot manipulation, IEEE/RSJ Int'l Conf. on Intelligent Robots and Systems (IROS 13), Tokyo, pp. 824–830. doi: 10.1109/IROS.2013.6696446

11 Foix S., Alenya G., Andrade-Cetto J. and Torras C. (2010): Object modeling using a ToF camera under an uncertainty reduction approach. IEEE Int'l Conf. on Robotics and Automation (ICRA 10), Anchorage, Alaska, pp. 1306–1312. doi: 10.1109/ROBOT.2010.5509197

12 Monso P., Alenya G. and Torras C. (2012): POMDP approach to robotized clothes separation. IEEE/RSJ Int'l Conf. on Intelligent Robots and Systems (IROS 12), Vilamoura, Portugal, pp. 1324–1329. doi: 10.1109/IROS.2012.6386011

13 Ulbrich S., Ruiz de Angulo V., Asfour T., Torras C. and Dillman R. (2012): Kinematic Bezier maps. IEEE Trans. on Systems, Man and Cybernetics: Part B, 42(4): 1215–1230. doi: 10.1109/TSMCB.2012.2188507
14 Ulbrich S., Ruiz de Angulo V., Asfour T., Torras C. and Dillman R. (2012): General robot kinematics decomposition without intermediate markers. IEEE Trans. on Neural Networks and Learning Systems, 23(4): 620–630. doi: 10.1109/TNNLS.2012.2183886
15 Martinez D., Alenya G., Jimenez P., Torras C., Rossmann J., Wantia N., Aksoy E.E., Haller S. and Piater J. (2014): Active Learning of Manipulation Sequences. IEEE Int'l Conf. on Robotics and Automation (ICRA 14), Hong-Kong.

4.22 Skill Development through Affordance-based Bootstrapping

Emre Ugur (Universität Innsbruck, AT)

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

Jure Zabkar (University of Ljubljana, SI)

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 algorithm for learning and consolidation of motor memory and study the space complexity of the representation in the experiments with humanoid robot Nao. Finally, we propose the integration of motor memory with sensor data into a common sensorimotor memory.

4.24 Project Report: RACE

Jianwei Zhang (Universität Hamburg, DE)

URL http://www.project-RACE.eu

In a dynamic and changing world, a robust, adaptive and effective artificial cognitive system (ACS) must have a high-level conceptual understanding of the world it inhabits. The overall aim of RACE is to develop an artificial cognitive system, embodied by a robot, able to build such a model of the world by storing and exploiting appropriate memories of its experiences. We will demonstrate how an ACS can evolve its model as a result of novel experiences; and show how such a model allows an ACS to better understand new situations enabling it to achieve its goals in new situations at a level of robustness and effectiveness previously not achievable. Experiences is recorded as semantic spatio-temporal structures connecting high-level representations, including goals, tasks and behaviours, via their constituents at lower levels down to the sensory and actuator level. In this way, experiences provide a detailed account of how the ACS has achieved past goals or how it has failed, and what sensory events have accompanied the activities. Conceptualisations are obtained by abstracting and generalising from experiences, extending task planning and execution beyond preconceived situations. Activities successfully carried out by the ACS for specific objects at specific locations may be generalised to activity concepts applicable to classes of objects at variable locations. Conceptualisations may also result in commonsense insights, e.g. about object behaviour on tilted surfaces. The project aims at the following main results: (i) Agents capable of storing experiences in their memory in terms of multi- level representations connecting actuator and sensory experiences with high- level semantic structures,
(ii) Methods for learning and conceptualising from experiences obtained from behaviour in realistically scaled real-world environments,
(iii) Robot systems demonstrating superior robustness and effectiveness caused by experience-based planning and behaviour adaptation within incompletely specified environments.
Results will be integrated and evaluated in an operational mobile platform with grasping facilities.

4.25 Project Report: STRANDS

Michael Zillich (TU Wien, AT)

Joint work of STRANDS, Consortium; Hawes, Nick
URL http://strands-project.eu

STRANDS will produce intelligent mobile robots that are able to run for months in dynamic human environments. We will provide robots with the longevity and behavioural robustness necessary to make them truly useful assistants in a wide range of domains. Such long-lived robots will be able to learn from a wider range of experiences than has previously been possible, creating a whole new generation of autonomous systems able to extract and exploit the structure in their worlds.

Our approach is based on understanding 3D space and how it changes over time, from milliseconds to months. We will develop novel approaches to extract spatio-temporal structure from sensor data gathered during months of autonomous operation. Extracted structure will include reoccurring 3D shapes, objects, people, and models of activity. We will also develop control mechanisms which exploit these structures to yield adaptive behaviour in highly demanding, realworld security and care scenarios.

5 Working Groups

5.1 Report Discussion Group 1

Alexandre Bernardino (Technical University – Lisboa, PT)

Joint work of All participants of the group

Scientific Questions

1. Where/How should uncertainty be dealt with in learning robots?
2. Computer Vision in Robotics (why robot vision seems somewhat disconnected from CV)?
3. How to construct a good ontology (for robot learning)?
4. What representations bridge low-level and high level?
5. Can we learn anything suitable to be used by higher levels?
6. Semantic vs low-level info
7. Can we use high-level knowledge to influence the low level?

Report. This report summarises the debate of Group 1 on the topics of theme A, listed above. The questions were not addressed by a specific order.

The starting point of the discussion was related to the utilisation of high-level knowledge in the lower levels of a cognitive architecture. In particular, the noise and percept instability in the low-level sensory sensory system were noted as major difficulties in information processing. To deal with noise some ideias were put forwards, in particular sequential (Bayes) probabilistic reasoning but maintaining logical representations from the high-level knowledge, although it is not yet clear how to go from the continuous/probabilistic information into symbols (where to put the threshold). If appropriate logical and temporal constraints are encoded, the large number of interpretations coming from the probabilistic representation cleans itself if one waits long enough. Therefore high-level models can be seen as a kind of filter that helps removing noise from the lower levels.

The next point under discussion was related to the application of computer vision in robotics. In robotics the images move constantly thus making interpretation more difficult. In some cases it is a matter of image retrieval (trying to identify known objects in the scene) but in other cases the robot itself may what to take an active role in searching for the objects. In this case ontologies, context and expectation can be helpful in the process. Anyway the problem is very complex and its seems difficult to tackle with only two levels of representation (low vs high level) because of big differences between them. More intermediate representations, with less variation among consecutive ones would probably simplify the planning levels. In particular some semantic levels could go lower in the hierarchy, even if names cannot be assigned to the managed symbols. Assigning names to symbols or having 1-to-1 mappings between words and symbols was considered not essential. Anything that can be labeled may carry semantic meaning.

Discussion then concentrated on how to build a good ontology. It was made a distinction between the purpose of the ontology: learning vs planning. Different purposes may demand ontologies with different characteristics. For learning it is important to have compositionally but no recursion. For planning it is important to have recursion. Then, appropriate translations are needed to convert among them. Good ontologies are also important for knowledge sharing (provide an organised way to share information), and for efficient reasoning. Another difficulty is related to different meanings of items in an ontology (example of the match box, candle and pin – the matchbox can be used as a support for the candle, which is not is common usage). For these cases we may need multiple ontologies and ways to switch between them. Also it is important to have languages supporting generalisation of concepts like ILP.

In the last point, it was discussed if ontologies are really needed or if we can just use all the stored experiments. One problem of using data alone is the need to define similarities between examples which is hard in high-dimensional spaces. In fact, is a similarity metric can be defined, it can also implicitly define an ontology, but needs to adjust to different situations and is not trivial. An example is obstacle avoidance. There is no concept of an obstacle (e.g. a chair) but just examples of failures to move associated to examples of chairs. Upon the observation of another chair, how to generalize ? By learning, we build a taxonomical representation "anything with bounding box of this shape is an obstacle". But again similarity is hard to assess, as largely debated in the book: The Subtlety of Sameness: A Theory and Computer Model of Analogy-making, by Robert Mills French.

5.2 Report Discussion Group 2

Alexandre Bernardino (Technical University – Lisboa, PT)

Joint work of All participants of the group

Scientific Questions

1. Domain adaption, knowledge transfer
2. Cross-modal learning
3. Learning strategies. Weakly supervised learning
4. What is the role of affordances (in robot learning, control and planning)?
5. One shot learning vs statistical learning
6. Learning over long (life) periods of time

Report. The discussion group addressed the questions in order. Below are listed the main points discussed for each one question.

1. The problem of domain adaption and knowledge transfer can be tackled by realising what is the transformation between the domains that may lead to the adaption of the behaviours. It can be as simple as estimating a parameter that maps the domains (e.g. calibration) or very hard in complex domains. Even in the simple one parameter case it may be hard to generalize. For example, consider shooting a ball of different weights.

If we use a football, the most efficient way is to kick it fast with the foot. However, if you try to generalize to a bowling ball, you need a very different strategy: hold with the hand, swing to gain momentum and then throw. There is continuous transition in the weight of the ball but a very significantly difference in the extreme cases.

2. Cross-modal learning is related to learning from different sensor modalities and creating associations between them. Having several sensor modalities is important to have a more complete perception of the environment – individual sensors may not be enough to sort out the relevant information in the environment. However, it brings many challenges like synchronisation between modalities, temporal segmentation, extraction of the right features, etc. The diversity of way to associate data between the different modalities may lead to high computational complexity.
3. Regarding learning strategies, the group debated whether it is beneficial to start learning in a simplified domain (easy to discover some basic principles) and then use them when learning in full sized domain (although some laws will have to be modified, refined to special cases). Example: learn about moving balls (snooker balls) in a limited plane with obstacles around. One could think of a staged learning approach: (i) start with a ball in infinite domain; (ii) then increase the number of balls; (iii) then include obstacles and limits on the plane. The approach seems reasonable but there are cases where things may work better otherwise. For example in chess teaching, adults start learning the movements of individual pieces, but for children it is better to teach the hole game from the start. Still in this point it was debated weakly supervised learning. In principle this method is able reduce the labelling effort but may be more sensitive to (weak)- label mistakes. Training data is critical.
4. Affordances are a complex concept with many alternative interpretations. One of the interpretations can be related to the pre-conditions for the application of actions on objects (object shape, position, orientation, etc). Under this interpretation it is possible to assess the key role of affordances in robot-learning, planning and control.
5. One shot learning vs statistical learning. It was discussed that one-shot learning may be enough with enough prior knowledge and/or simple domains. For instance, children can learn to recognise giraffes from a single picture. However, a giraffe is a very distinctive animal with respect to the other. In cases where the distinction between classes is more ambiguous, statistical learning and many more examples may be required.
6. The problem of learning over long life periods of time was the last point of discussion on this session. The most critical aspect of this type of learning was related to knowledge management. Learning over long period of time require to compress the examples acquired (it is impossible to keep all the examples in memory), so issues like forgetting and remembering and of great relevance and not very much explored in the literature. Other aspect related to continual learning it how to explore the world to learn fast. This is sometimes denoted as active learning. With adequate exploration strategies, a robot can learn more efficiently. Finally, having huge amounts of data may lead to overfitting (learning too specific examples and do not generalize well). To prevent this effect, classical machine learning methodologies can be used, e.g. cross-validation.

5.3 Report Discussion Group 4a

Laurent Orseau (AgroParisTech – Paris, FR)

Joint work of Bernd Neumann; Laurent Orseau; Georgi Stojanov; Markus Vincze

Participants of the group: Bernd Neumann, Laurent Orseau, Georgi Stojanov, Markus Vincze.

1. The question was whether we should adopt a systemic perspective of all the topics discussed during the seminar, i.e. whether we should keep in mind the global picture and the long term goals of robotics. We (the group of 4 participants) unanimously agreed that it was preferable.
2. The underlying question is: "What is the level of autonomy that we want for a robot?". Should robots be able to modify themselves entirely? The example of the Gödel Machine [1] was taken as an example of such an agent. Self-modification is related to learning since learning modifies the parameters of the underlying system. For moderately intelligent robots such as service robots, it does not seem that full self-modification is useful. However, it must be noted that (human-level) intelligent robots will nonetheless be able to modify themselves entirely, possibly by indirect means like asking someone else.
3. The framework presented in [2] makes a clear distinction between the source code and the memory of the agent: Knowledge and reasoning are separated into two entities. Although it is a practical separation for the cited work, it is not clear that it is a necessary or even a useful assumption for robotics.y It must be noted that the human brain actually takes the completely opposite approach: memory and processes are completely entangled.
4. Common sense has been a desirable feature since the beginnings of robotics, but has never been properly tackled. Everyone is focusing on more short-term tasks. According to some in the discussion group, ontologies are probably not going to solve this problem, as it seems unlikely that we can handcraft all common sense knowledge in advance. So we probably need something different.

   Learning the (intuition of the) laws of physics can be important to predict the effects of actions like pulling a notepad on which there is a pen. Will the pen roll and fall, or will it come with the notepad? Humans seem to reason by predicting the consequences of actions, but the kind of reasoning seem to be context-dependent (e.g., depending on what to focus on), and so it is not clear that common-sense is always about prediction.

   Learning common sense seems to be a big challenge. The group suggested the possibility to build a robot that, in a first phase, is meant to learn without a particular goal, so as to accumulate common-sense, much like Pierre-Yves Oudeyer's curiosity learning robots [4], or Laurent Orseau's knowledge-seeking agents [3], the latter of which chooses its actions so as to maximise the entropy of the possible outcomes, in order to gain as much information about the world as possible. In the second phase, copies of the robot could be specialised for various tasks suitable for a service robot.
5. Designing rewards can be very complicated, in particular if we want autonomous agents. The example of a gliding agent in a maze was taken: If we want the agent to move around the maze, it is not sufficient to merely give a reward to the agent for moving forward and punishment for hitting walls, as the agent may then simply turn in circles, which indeed maximises the expected reward. This shows that designing a reward function is far from trivial. In particular, for a service robot that can be rewarded and punished through a

remote-control, it should require only moderate intelligence and common sense for the robot to realise that it should acquire the remote-control to press the reward button itself. The question of designing a good reward function becomes quite complicated when we consider multidimensional rewards, in particular when considering the interactions between various rewards. It was also discussed whether rewards should be defined once and for all or if rewards could change in time, seemingly by analogy with how humans change their preferences. However, it was not clear whether it is the rewards or the values that change.

5.4 Report Discussion Group 4b

Sebastian Rockel (Universität Hamburg, DE)

Joint work of Rockel, Sebastian; Stock, Sebastian; Konecny, Stefan; Saffiotti, Alessandro; Lehmann, Jos; Hotz, Lothar; Bratko, Ivan; Möller, Ralf; Cohn, Anthony

Participants of the group: Ivan Bratko, Anthony Cohn, Alessandro Saffiotti, Ralf Möller, Lothar Hotz, Jos Lehmann, Sebastian Rockel, Sebastian Stock, Stefan Konecny.

Scientific Questions

1. Should we take a system perspective on the above questions?
2. Theoretical framework for learning agents
3. Self-modifying agents, representations vs. processes
4. Learning common sense, meta-knowledge

Report. 1 and 4 – Learning common sense and learning meta-knowledge should be viewed at separately as they are different types of knowledge. Although meta-knowledge does include some common sense knowledge. Examples for common sense would be how to use tools (and if at all). For learning common sense knowledge it is required being able to represent qualitatively physics.

There are different representations of common sense knowledge: e.g. learning from infants vs. learning with formulas. It is also important to state that humans share common sense with animals. An example for meta-knowledge on the contrary would be: "Knowing that I don't know". Furthermore the discussion group points out that uncertainty has a notable relation to meta-knowledge.

A valid robotics related question is: "How should robots be built up with an understanding capability of common sense knowledge?" Common sense knowledge as a separate form of knowledge (besides spatial, temporal etc.). Learning common sense knowledge once and transfer it to multiple (different) robots is a desirable goal when it comes to sharing knowledge between robots. Learning common sense is lacking negative examples. Thus dedicated learning methods, such as clustering, have to be applied.

A wide consensus within the group is the openness of a definition for "common sense". A direct question to this is: "If at all to learn common sense or rather define it once (and use it again)?" An agreed definition proposal within the group is (common sense): Everything learned (by a child) out of pure curiosity is considered to be common sense knowledge. Furthermore Common sense is more than naive physics reasoning, e.g. following statement is also considered to be common sense: "You get a cold outside when not dressed appropriately in winter."

Present knowledge representation and learning systems are not well suited when faced with common sense reasoning, e.g. using ontologies. Common sense in AI is not explored well as of today. Learning it is certainly a desired capability of a robot, but not much has been done yet in this field yet. Although it is an attractive way to acquire it by learning. In principle human common sense can be shared with robots.

In summary, common sense is useful for robots, especially in domestic environments. It is not usable as of today (in general) with present tools, only in constrained scenarios with a constrained knowledge base.

References

1. Jürgen Schmidhuber. *Ultimate Cognition à la Gödel*. Cognitive Computation 2(1), pp. 177–193, 2009. doi: 10.1007/s12559-009-9014-y.
2. Laurent Orseau and Mark Ring. *Self-Modification and Mortality in Artificial Agents*. Artificial General Intelligence, Lecture Notes in Computer Science 6830, pp. 1–10, 2011, doi: 10.1007/978-3-642-22887-2-1.
3. Laurent Orseau, Tor Lattimore and Marcus Hutter. *Universal Knowledge-Seeking Agents for Stochastic Environments*. Proc. 24th International Conf. on Algorithmic Learning Theory (ALT'13), Singapore, LNAI 8139, pp. 158–172, 2013, doi: 10.1007/978-3-642-40935-6-12.
4. Adrien Baranes and Pierre-Yves Oudeyer. *Active Learning of Inverse Models with Intrinsically Motivated Goal Exploration in Robots*. Robotics and Autonomous Systems 61(1), 2013, pp. 69–73, doi: 10.1016/j.robot.2012.05.008.

Participants

- Michael Beetz
Universität Bremen, DE
- Sven Behnke
Universität Bonn, DE
- Alexandre Bernardino
Technical Univ. – Lisboa, PT
- Mustafa Blerim
The American University of Paris, FR
- Richard Bowden
University of Surrey, GB
- Ivan Bratko
University of Ljubljana, SI
- Francois Bremond
INRIA Sophia Antipolis – Méditerranée, FR
- Anthony G. Cohn
University of Leeds, GB
- Luc De Raedt
KU Leuven, BE
- Krishna Sandeep Reddy Dubba
University of Leeds, GB
- Martin Günther
Universität Osnabrück, DE
- Manfred Hild
HU Berlin, DE
- Vaclav Hlavac
Czech Technical University, CZ
- David C. Hogg
University of Leeds, GB
- Lothar Hotz
Universität Hamburg, DE
- Lorenzo Jamone
Technical Univ. – Lisboa, PT
- Stefan Konecny
University of Örebro, SE
- Marek S. Kopicki
University of Birmingham, GB
- Jos Lehmann
Universität Hamburg, DE
- Ales Leonardis
University of Birmingham, GB
- Masoumeh Mansouri
University of Örebro, SE
- Ralf Moeller
TU Hamburg-Harburg, DE
- Bernd Neumann
Universität Hamburg, DE
- Davide Nitti
KU Leuven, BE
- Laurent Orseau
AgroParisTech – Paris, FR
- Pierre-Yves Oudeyer
INRIA – Bordeaux, FR
- Federico Pecora
University of Örebro, SE
- Sebastian Rockel
Universität Hamburg, DE
- Alessandro Saffiotti
University of Örebro, SE
- Luis Seabra Lopes
University of Aveiro, PT
- Muralikrishna Sridhar
University of Leeds, GB
- Luc Steels
Free University of Brussels, BE
- Sebastian Stock
Universität Osnabrück, DE
- Georgi Stojanov
The American University of Paris, FR
- Aryana Tavanai
University of Leeds, GB
- Carme Torras
UPC – Barcelona, ES
- Emre Ugur
Universität Innsbruck, AT
- Markus Vincze
TU Wien, AT
- Jure Zabkar
University of Ljubljana, SI
- Jianwei Zhang
Universität Hamburg, DE
- Michael Zillich
TU Wien, AT