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Activity Report 2016

Project-Team FLOWERS

Flowing Epigenetic Robots and Systems

RESEARCH CENTER
Bordeaux - Sud-Ouest

THEME
Robotics and Smart environments

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Creation of the Team: 2008 April 01, updated into Project-Team: 2011 January 01

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1. Members

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2. Overall Objectives

2.1. Overall Objectives

Can a robot learn like a child? Can it learn new skills and new knowledge in an unknown and changing environment? How can it discover its body and its relationships with the physical and social environment? How can its cognitive capacities continuously develop without the intervention of an engineer? What can it learn through natural social interactions with humans?

These are the questions that are being investigated in the FLOWERS research team at Inria Bordeaux Sud-Ouest. Rather than trying to imitate the intelligence of adult humans like in the field of Artificial Intelligence, we believe that trying to reconstruct the processes of development of the child's mind will allow for more adaptive, more robust and more versatile machines. This approach is called developmental robotics, or epigenetic robotics, and imports concepts and theories from developmental psychology. As most of these theories are not formalized, this implies a crucial computational modeling activity, which in return provides means to assess the internal coherence of theories and sketch new hypothesis about the development of the human child's sensorimotor and cognitive abilities.

Our team focuses in particular on the study of developmental constraints that allow for efficient open-ended learning of novel sensorimotor and interaction skills in embodied systems. In particular, we study constraints that guide exploration in large sensorimotor spaces:

- Mechanisms of intrinsically motivated exploration and active learning, including artificial curiosity, allowing in particular to self-organize developmental trajectories and collect efficiently learning data;
- Mechanisms of adequately constrained optimization and statistical inference for sensorimotor skill acquisition (e.g. for optimizing motor policies in real robots);
- Mechanisms for social learning, e.g. learning by imitation or demonstration, which implies both issues related to machine learning and human-robot interaction;
- Constraints related to embodiment, in particular through the concept of morphological computation, as well as the structure of motor primitives/muscle synergies that can leverage the properties of morphology and physics for simplifying motor control and perception;
- Maturational constraints which, coupled with the other constraints, can allow the progressive release of novel sensorimotor degrees of freedom to be explored;

We also study how these constraints on exploration can allow a robot to bootstrap multimodal perceptual abstractions associated to motor skills, in particular in the context of modelling language acquisition as a developmental process grounded in action.

Among the developmental principles that characterize human infants and can be used in developmental robots, FLOWERS focuses on the following three principles:

- **Exploration is progressive.** The space of skills that can be learnt in real world sensorimotor spaces is so large and complicated that not everything can be learnt at the same time. Simple skills are learnt first, and only when they are mastered, new skills of progressively increasing difficulty become the behavioural focus;
- **Internal representations are (partially) not innate but learnt and adaptive.** For example, the body map, the distinction self/non-self and the concept of "object" are discovered through experience with initially uninterpreted sensors and actuators, guided by experience, the overall pre-determined connection structure of the brain, as well as a small set of simple innate values or preferences.
- **Exploration can be self-guided and/or socially guided.** On the one hand, internal and intrinsic motivation systems regulate and organize spontaneous exploration; on the other hand, exploration can be guided through social learning and interaction with caretakers.

2.1.1. Research axis

The work of FLOWERS is organized around the following axis:

- **Curiosity-driven exploration and sensorimotor learning:** intrinsic motivation are mechanisms that have been identified by developmental psychologists to explain important forms of spontaneous exploration and curiosity. In FLOWERS, we try to develop computational intrinsic motivation systems, and test them on robots, allowing to regulate the growth of complexity in exploratory behaviours. These mechanisms are studied as active learning mechanisms, allowing to learn efficiently in large inhomogeneous sensorimotor spaces;
- **Cumulative learning of sensorimotor skills:** FLOWERS develops machine learning algorithms that can allow embodied machines to acquire cumulatively sensorimotor skills. In particular, we develop optimization and reinforcement learning systems which allow robots to discover and learn dictionaries of motor primitives, and then combine them to form higher-level sensorimotor skills.
- **Natural and intuitive social learning:** FLOWERS develops interaction frameworks and learning mechanisms allowing non-engineer humans to teach a robot naturally. This involves two sub-themes: 1) techniques allowing for natural and intuitive human-robot interaction, including simple ergonomic interfaces for establishing joint attention; 2) learning mechanisms that allow the robot to use the guidance hints provided by the human to teach new skills;
- **Discovering and abstracting the structure of sets of uninterpreted sensors and motors:** FLOWERS studies mechanisms that allow a robot to infer structural information out of sets of sensorimotor channels whose semantics is unknown, for example the topology of the body and the sensorimotor contingencies (propriocetive, visual and acoustic). This process is meant to be open-ended, progressing in continuous operation from initially simple representations to abstract concepts and categories similar to those used by humans.
- Body design and role of the body in sensorimotor and social development We study how the physical properties of the body (geometry, materials, distribution of mass, growth, ...) can impact the acquisition of sensorimotor and interaction skills. This requires to consider the body as an experimental variable, and for this we develop special methodologies for designing and evaluating rapidly new morphologies, especially using rapid prototyping techniques like 3D printing.
- **Intelligent Tutoring Systems:**FLOWERS develops methods for online personalization of teaching sequences for educational software and MOOCs. This work builds on top of online optimization methods and motivational research previously developed.

3. Research Program

3.1. Research Program

Research in artificial intelligence, machine learning and pattern recognition has produced a tremendous amount of results and concepts in the last decades. A blooming number of learning paradigms - supervised, unsupervised, reinforcement, active, associative, symbolic, connectionist, situated, hybrid, distributed learning... - nourished the elaboration of highly sophisticated algorithms for tasks such as visual object recognition, speech recognition, robot walking, grasping or navigation, the prediction of stock prices, the evaluation of risk for insurances, adaptive data routing on the internet, etc... Yet, we are still very far from being able to build machines capable of adapting to the physical and social environment with the flexibility, robustness, and versatility of a one-year-old human child.

Indeed, one striking characteristic of human children is the nearly open-ended diversity of the skills they learn. They not only can improve existing skills, but also continuously learn new ones. If evolution certainly provided them with specific pre-wiring for certain activities such as feeding or visual object tracking, evidence shows that there are also numerous skills that they learn smoothly but could not be "anticipated" by biological evolution, for example learning to drive a tricycle, using an electronic piano toy or using a video game joystick. On the contrary, existing learning machines, and robots in particular, are typically only able to learn a single pre-specified task or a single kind of skill. Once this task is learnt, for example walking with two legs, learning is over. If one wants the robot to learn a second task, for example grasping objects in its visual field, then an engineer needs to re-program manually its learning structures: traditional approaches to task-specific machine/robot learning typically include engineer choices of the relevant sensorimotor channels, specific design of the reward function, choices about when learning begins and ends, and what learning algorithms and associated parameters shall be optimized.

As can be seen, this requires a lot of important choices from the engineer, and one could hardly use the term "autonomous" learning. On the contrary, human children do not learn following anything looking like that process, at least during their very first years. Babies develop and explore the world by themselves, focusing their interest on various activities driven both by internal motives and social guidance from adults who only have a folk understanding of their brains. Adults provide learning opportunities and scaffolding, but eventually young babies always decide for themselves what activity to practice or not. Specific tasks are rarely imposed to them. Yet, they steadily discover and learn how to use their body as well as its relationships with the physical and social environment. Also, the spectrum of skills that they learn continuously expands in an organized manner: they undergo a developmental trajectory in which simple skills are learnt first, and skills of progressively increasing complexity are subsequently learnt.

A link can be made to educational systems where research in several domains have tried to study how to provide a good learning experience to learners. This includes the experiences that allow better learning, and in which sequence they must be experienced. This problem is complementary to that of the learner that tries to learn efficiently, and the teacher here has to use as efficiently the limited time and motivational resources of the learner. Several results from psychology [112] and neuroscience [22] have argued that the human brain feels intrinsic pleasure in practicing activities of optimal difficulty or challenge. A teacher must exploit such activities to create positive psychological states of flow [124].

A grand challenge is thus to be able to build robotic machines that possess this capability to discover, adapt and develop continuously new know-how and new knowledge in unknown and changing environments, like human children. In 1950, Turing wrote that the child's brain would show us the way to intelligence: "Instead of trying to produce a program to simulate the adult mind, why not rather try to produce one which simulates the child's" [174]. Maybe, in opposition to work in the field of Artificial Intelligence who has focused on mechanisms trying to match the capabilities of "intelligent" human adults such as chess playing or natural language dialogue [134], it is time to take the advice of Turing seriously. This is what a new field, called developmental (or epigenetic) robotics, is trying to achieve [145] [178]. The approach of developmental robotics consists in importing and implementing concepts and mechanisms from developmental psychology [148], cognitive linguistics [123], and developmental cognitive neuroscience [139] where there has been a considerable amount of research and theories to understand and explain how children learn and develop. A number of general principles are underlying this research agenda: embodiment [116] [156], grounding [132], situatedness [105], self-organization [172] [158], enaction [176], and incremental learning [119].

Among the many issues and challenges of developmental robotics, two of them are of paramount importance: exploration mechanisms and mechanisms for abstracting and making sense of initially unknown sensorimotor channels. Indeed, the typical space of sensorimotor skills that can be encountered and learnt by a developmental robot, as those encountered by human infants, is immensely vast and inhomogeneous. With a sufficiently rich environment and multimodal set of sensors and effectors, the space of possible sensorimotor activities is simply too large to be explored exhaustively in any robot's life time: it is impossible to learn all possible skills and represent all conceivable sensory percepts. Moreover, some skills are very basic to learn, some other very complicated, and many of them require the mastery of others in order to be learnt. For example, learning to manipulate a piano toy requires first to know how to move one's hand to reach the piano and how to touch specific parts of the toy with the fingers. And knowing how to move the hand might require to know how to track it visually.

Exploring such a space of skills randomly is bound to fail or result at best on very inefficient learning [153]. Thus, exploration needs to be organized and guided. The approach of epigenetic robotics is to take inspiration from the mechanisms that allow human infants to be progressively guided, i.e. to develop. There are two broad classes of guiding mechanisms which control exploration:

1. **internal guiding mechanisms,** and in particular intrinsic motivation, responsible of spontaneous exploration and curiosity in humans, which is one of the central mechanisms investigated in FLOWERS, and technically amounts to achieve online active self-regulation of the growth of complexity in learning situations;
2. **social learning and guidance,** a learning mechanisms that exploits the knowledge of other agents in the environment and/or that is guided by those same agents. These mechanisms exist in many different forms like emotional reinforcement, stimulus enhancement, social motivation, guidance, feedback or imitation, some of which being also investigated in FLOWERS;

3.1.1. Internal guiding mechanisms

In infant development, one observes a progressive increase of the complexity of activities with an associated progressive increase of capabilities [148], children do not learn everything at one time: for example, they first learn to roll over, then to crawl and sit, and only when these skills are operational, they begin to learn how to stand. The perceptual system also gradually develops, increasing children perceptual capabilities other time while they engage in activities like throwing or manipulating objects. This make it possible to learn to identify objects in more and more complex situations and to learn more and more of their physical characteristics.

Development is therefore progressive and incremental, and this might be a crucial feature explaining the efficiency with which children explore and learn so fast. Taking inspiration from these observations, some roboticists and researchers in machine learning have argued that learning a given task could be made much easier for a robot if it followed a developmental sequence and "started simple" [108] [127]. However, in these experiments, the developmental sequence was crafted by hand: roboticists manually build simpler versions of a complex task and put the robot successively in versions of the task of increasing complexity. And when they wanted the robot to learn a new task, they had to design a novel reward function.

Thus, there is a need for mechanisms that allow the autonomous control and generation of the developmental trajectory. Psychologists have proposed that intrinsic motivations play a crucial role. Intrinsic motivations are mechanisms that push humans to explore activities or situations that have intermediate/optimal levels of novelty, cognitive dissonance, or challenge [112] [124] [126]. The role and structure of intrinsic motivation in humans have been made more precise thanks to recent discoveries in neuroscience showing the implication of dopaminergic circuits and in exploration behaviours and curiosity [125] [136] [166]. Based on this, a number of researchers have began in the past few years to build computational implementation of intrinsic motivation [153] [154] [164] [111] [137] [146] [165]. While initial models were developed for simple simulated worlds, a current challenge is to manage to build intrinsic motivation systems that can efficiently drive exploratory behaviour in high-dimensional unprepared real world robotic sensorimotor spaces [154], [153], [155], [163]. Specific and complex problems are posed by real sensorimotor spaces, in particular due to the fact that they are both high-dimensional as well as (usually) deeply inhomogeneous. As an example for the latter issue, some regions of real sensorimotor spaces are often unlearnable due to inherent stochasticity or difficulty, in which case heuristics based on the incentive to explore zones of maximal unpredictability or uncertainty, which are often used in the field of active learning [120] [133] typically lead to catastrophic results. The issue of high dimensionality does not only concern motor spaces, but also sensory spaces, leading to the problem of correctly identifying, among typically thousands of quantities, those latent variables that have links to behavioral choices. In FLOWERS, we aim at developing intrinsically motivated exploration mechanisms that scale in those spaces, by studying suitable abstraction processes in conjunction with exploration strategies.

3.1.2. Socially Guided and Interactive Learning

Social guidance is as important as intrinsic motivation in the cognitive development of human babies [148]. There is a vast literature on learning by demonstration in robots where the actions of humans in the environment are recognized and transferred to robots [107]. Most such approaches are completely passive: the human executes actions and the robot learns from the acquired data. Recently, the notion of interactive learning has been introduced in [173], [113], motivated by the various mechanisms that allow humans to socially guide a robot [160]. In an interactive context the steps of self-exploration and social guidances are not separated and a robot learns by self exploration and by receiving extra feedback from the social context [173], [142] [147].

Social guidance is also particularly important for learning to segment and categorize the perceptual space. Indeed, parents interact a lot with infants, for example teaching them to recognize and name objects or characteristics of these objects. Their role is particularly important in directing the infant attention towards objects of interest that will make it possible to simplify at first the perceptual space by pointing out a segment of the environment that can be isolated, named and acted upon. These interactions will then be complemented by the children own experiments on the objects chosen according to intrinsic motivation in order to improve the knowledge of the object, its physical properties and the actions that could be performed with it.

In FLOWERS, we are aiming at including intrinsic motivation system in the self-exploration part thus combining efficient self-learning with social guidance [150], [151]. We also work on developing perceptual capabilities by gradually segmenting the perceptual space and identifying objects and their characteristics through interaction with the user [32] and robots experiments [138]. Another challenge is to allow for more flexible interaction protocols with the user in terms of what type of feedback is provided and how it is provided [144].

Exploration mechanisms are combined with research in the following directions:

3.1.3. Cumulative learning, reinforcement learning and optimization of autonomous skill learning

FLOWERS develops machine learning algorithms that can allow embodied machines to acquire cumulatively sensorimotor skills. In particular, we develop optimization and reinforcement learning systems which allow robots to discover and learn dictionaries of motor primitives, and then combine them to form higher-level sensorimotor skills.

3.1.4. Autonomous perceptual and representation learning

In order to harness the complexity of perceptual and motor spaces, as well as to pave the way to higher-level cognitive skills, developmental learning requires abstraction mechanisms that can infer structural information out of sets of sensorimotor channels whose semantics is unknown, discovering for example the topology of the body or the sensorimotor contingencies (proprioceptive, visual and acoustic). This process is meant to be open- ended, progressing in continuous operation from initially simple representations towards abstract concepts and categories similar to those used by humans. Our work focuses on the study of various techniques for:

- autonomous multimodal dimensionality reduction and concept discovery;
- incremental discovery and learning of objects using vision and active exploration, as well as of auditory speech invariants;
- learning of dictionaries of motion primitives with combinatorial structures, in combination with linguistic description;
- active learning of visual descriptors useful for action (e.g. grasping);

3.1.5. Embodiment and maturational constraints

FLOWERS studies how adequate morphologies and materials (i.e. morphological computation), associated to relevant dynamical motor primitives, can importantly simplify the acquisition of apparently very complex skills such as full-body dynamic walking in biped. FLOWERS also studies maturational constraints, which are mechanisms that allow for the progressive and controlled release of new degrees of freedoms in the sensorimotor space of robots.

3.1.6. Discovering and abstracting the structure of sets of uninterpreted sensors and motors

FLOWERS studies mechanisms that allow a robot to infer structural information out of sets of sensorimotor channels whose semantics is unknown, for example the topology of the body and the sensorimotor contingencies (proprioceptive, visual and acoustic). This process is meant to be open-ended, progressing in continuous operation from initially simple representations to abstract concepts and categories similar to those used by humans.

4. Application Domains

4.1. Application Domains

Cognitive Sciences The computational modelling of life-long learning and development mechanisms achieved in the team centrally targets to contribute to our understanding of the processes of sensorimotor, cognitive and social development in humans. In particular, it provides a methodological basis to analyze the dynamics of the interaction across learning and inference processes, embodiment and the social environment, allowing to formalize precise hypotheses and later on test them in experimental paradigms with animals and humans. A paradigmatic example of this activity is the Neurocuriosity project achieved in collaboration with the cognitive neuroscience lab of Jacqueline Gottlieb, where theoretical models of the mechanisms of information seeking, active learning and spontaneous exploration have been developped in coordination with experimental evidence and investigation, see https://flowers.inria.fr/neurocuriosityproject/.

Personal and lifelong learning robotics Many indicators show that the arrival of personal robots in homes and everyday life will be a major fact of the 21st century. These robots will range from purely entertainment or educative applications to social companions that many argue will be of crucial help in our society. Yet, to realize this vision, important obstacles need to be overcome: these robots will have to evolve in unpredictable homes and learn new skills in a lifelong manner while interacting with non-engineer humans after they left factories, which is out of reach of current technology. In this context, the refoundation of intelligent systems that developmental robotics is exploring opens potentially novel horizons to solve these problems. In particular, this application domain requires advances in artificial intelligence that go beyond the current state-of-the-art in fields like deep learning. Currently these techniques require tremendous amounts of data in order to function properly, and they are severaly limited in terms of incremental and transfer learning. One of our goals is to drastically reduce the amount of data required in order for this very potent field to work. We try to achieve this by making neural networks aware of their knowledge, i.e. we introduce the concept of uncertainty, and use it as part of intrinsically motivated multitask learning architectures, and combined with techniques of learning by imitation.

Human-Robot Collaboration. Robots play a vital role for industry and ensure the efficient and competitive production of a wide range of goods. They replace humans in many tasks which otherwise would be too difficult, too dangerous, or too expensive to perform. However, the new needs and desires of the society call for manufacturing system centered around personalized products and small series productions. Human-robot collaboration could widen the use of robot in this new situations if robots become cheaper, easier to program and safe to interact with. The most relevant systems for such applications would follow an expert worker and works with (some) autonomy, but being always under supervision of the human and acts based on its task models.

Environment perception in intelligent vehicles. When working in simulated traffic environments, elements of FLOWERS research can be applied to the autonomous acquisition of increasingly abstract representations of both traffic objects and traffic scenes. In particular, the object classes of vehicles and pedestrians are if interest when considering detection tasks in safety systems, as well as scene categories (”scene context”) that have a strong impact on the occurrence of these object classes. As already indicated by several investigations in the field, results from present-day simulation technology can be transferred to the real world with little impact on performance. Therefore, applications of FLOWERS research that is suitably verified by real-world benchmarks has direct applicability in safety-system products for intelligent vehicles.

Automated Tutoring Systems. Optimal teaching and efficient teaching/learning environments can be applied to aid teaching in schools aiming both at increase the achievement levels and the reduce time needed. From a practical perspective, improved models could be saving millions of hours of students’ time (and effort) in learning. These models should also predict the achievement levels of students in order to influence teaching practices.

5. Highlights of the Year

5.1. Highlights of the Year

The Flowers team spin-off company Pollen Robotics was created in may 2016, targeting to develop and commercialize technologies for entertainment robotics: http://pollen-robotics.com/en/

Didier Roy was award the prize Serge Hocquenguem for his work on educational robotics, http://psh.aid-creem.org/spip.php?rubrique1 et http://binaire.blog.lemonde.fr/2016/12/09/pourquoi-didier-et-eva-jouent-avec-le-meme-robot/

Sébastien Forestier, Yoan Mollard, Damien Caselli and Pierre-Yves Oudeyer obtained the notable mention demonstration award (2nd place) at the NIPS 2016 conference for their demonstration on Autonomous exploration, active learning and human guidance with open-source Poppy humanoid robot platform and Explauto library https://hal.inria.fr/hal-01404399/document

PY. Oudeyer and M. Lopes co-organized with J. Gottlieb and T. Gliga the Second Interdisciplinary Symposium on Information-Seeking, Curiosity and Attention (Neurocuriosity 2016) in London, gathering 150 researchers from neuroscience, psychology, education and machine learning/computational modelling. This was achieved in the context of the associated team Neurocuriosity. Web: https://openlab-flowers.inria.fr/t/second-interdisciplinary-symposium-on-information-seeking-curiosity-and-attention-neurocuriosity-2016/187

PY. Oudeyer and M. Lopes were awarded a 3 year-long HFSP grant with J. Gottlieb (Univ. Columbia, US) and C. Kidd (Univ. Rochester, US) for a research program targeting the understanding of active exploration in humans and monkeys through experimentation and modelling. Web: https://flowers.inria.fr/neurocuriosityproject/.

PY. Oudeyer was awarded the Lifetime Achievement Award from the Evolutionary Linguistics Association.

6. New Software and Platforms

6.1. Poppy project

6.1.1. HiPi Board

FUNCTIONAL DESCRIPTION

Hipi is a board to control robots on Raspberry Pi. It is an extension of the Pixl board with the following features:

- A DC/DC power converter from 12V (motor) to 5V (Raspberry Pi) at 3A.
- A stereo audio amplifier 3W.
- A MPU9250 central motion unit .
- A RS232 and a RS485 bus connected to the Raspberry Pi by SPI for driving MX and RX Dynamixel motor series.

This board will be integrated soon in the new head of the Poppy Humanoid and Poppy Torso.

Using the Raspberry Pi for every Poppy robots will simplify the hardware complexity (we maintain 4 types of embedded boards, with different Linux kernel and configurations) and improve the usage and installation of new robots.

- Contact: Theo Segonds
- URL: https://forum.poppy-project.org/t/poppy-1-1-hipi/2137

6.1.2. IKPy

Inverse Kinematics Python Library

FUNCTIONAL DESCRIPTION

IKPy is a Python Inverse Kinematics library, designed to be simple to use and extend. It provides Forward and Inverse kinematics functionality, bundled with helper tools such as 3D plotting of the kinematics chains. Being written entirely in Python, IKPy is lightweight and is based on numpy and scipy for fast optimization. IKPy is compatible with many robots, by automatically parsing URDF files. It also supports other (such as DH-parameters) and custom representations. Moreover, it provides a framework to easily implement new Inverse Kinematics strategies. Originally developed for the Poppy project, it can also be used as a standalone library.

- Contact: Pierre Manceron
- URL: https://github.com/Phylliade/ikpy

6.1.3. Pixl Board

FUNCTIONAL DESCRIPTION

Pixl is a tiny board used to create low cost robots based on Raspberry Pi board and Dynamixel XL-320 motors. This board has 2 main features:

- The power part, allowing the user to plug a 7.5V AC/DC converter or a battery directly into the Pixl. This power is distributed to all XL320 motors and is converted to 5V for the Raspberry Pi board.
- The communication part, which converts full duplex to half duplex and vice-versa. The half duplex part switch between RX and TX automatically. Another connector allows the user to connect his XL320 network.

The board is used in the Poppy Ergo Jr robot.

- Contact: Theo Segonds
- URL: https://github.com/poppy-project/pixl

6.1.4. Poppy

FUNCTIONAL DESCRIPTION

The Poppy Project team develops open-source 3D printed robots platforms based on robust, flexible, easy-to-use and reproduce hardware and software. In particular, the use of 3D printing and rapid prototyping technologies is a central aspect of this project, and makes it easy and fast not only to reproduce the platform, but also to explore morphological variants. Poppy targets three domains of use: science, education and art.

In the Poppy project we are working on the Poppy System which is a new modular and open-source robotic architecture. It is designed to help people create and build custom robots. It permits, in a similar approach as Lego, building robots or smart objects using standardized elements.

Poppy System is a unified system in which essential robotic components (actuators, sensors...) are independent modules connected with other modules through standardized interfaces:

- Unified mechanical interfaces, simplifying the assembly process and the design of 3D printable parts.
- Unified communication between elements using the same connector and bus for each module.
- Unified software, making it easy to program each module independently.

Our ambition is to create an ecosystem around this system so communities can develop custom modules, following the Poppy System standards, which can be compatible with all other Poppy robots.

- Participants: Pierre Rouanet, Matthieu Lapeyre, Jonathan Grizou and Pierre-Yves Oudeyer
- Contact: Pierre-Yves Oudeyer
- URL: https://www.poppy-project.org/

6.1.5. Poppy Ergo Jr

FUNCTIONAL DESCRIPTION

Poppy Ergo Jr is an open hardware robot developed by the Poppy Project to explore the use of robots in classrooms for learning robotic and computer science.

It is available as a 6 or 4 degrees of freedom arm designed to be both expressive and low-cost. This is achieved by the use of FDM 3D printing and low cost Robotis XL-320 actuators. A Raspberry Pi camera is attached to the robot so it can detect object, faces or QR codes.

The Ergo Jr is controlled by the Pypot library and runs on a Raspberry pi 2 or 3 board. Communication between the Raspberry Pi and the actuators is made possible by the Pixl board we have designed.

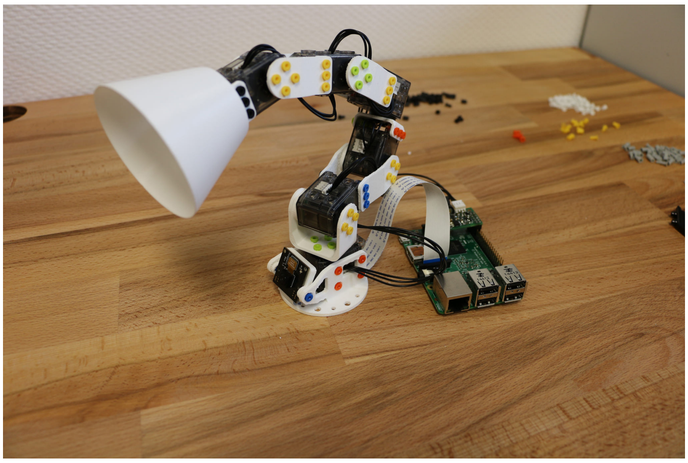

Figure 1. Poppy Ergo Jr, 6-DoFs arm robot for education

The Poppy Ergo Jr robot has several 3D printed tools extending its capabilities. There are currently the lampshade, the gripper and a pen holder.

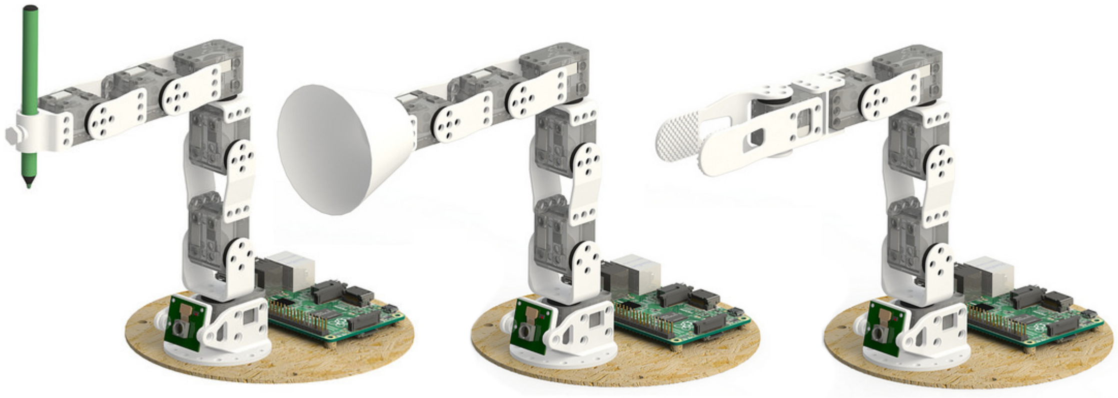

Figure 2. The available Ergo Jr tools: a pen holder, a lampshade and a gripper

With the release of a new Raspberry Pi board early 2016, the Poppy Ergo Jr disk image was updated to support Raspberry Pi 2 and 3 boards. The disk image can be used seamlessly with a board or the other.

- Contact: Theo Segonds
- URL: https://github.com/poppy-project/poppy-ergo-jr

6.1.6. Poppy Ergo Jr Installer

FUNCTIONAL DESCRIPTION

An alternative way to install the Ergo Jr robot software is made available using containers.

Users can own their own operating system installation, then add the Ergo Jr required software in a sandboxed environment. This results in a non-intrusive installation on the host system.

Docker containers implementation were used, and image is hosted at Docker Hub.

- Contact: Damien Caselli
- URL: https://hub.docker.com/r/poppycommunity/ergo-jr/

6.1.7. Poppy Ergo Jr Simulator

FUNCTIONAL DESCRIPTION

Poppy Project, through Poppy Education, wants users to get used to robotics, even without owning a physical robot.

For that purpose, Poppy Project team created a dummy robot in Pypot that is meant to be used in conjunction with a consumer application. We choose to develop a web hosted application using a 3D engine (Threejs) to render the robot.

Our ambition is to have a completely standalone simulated robot with physics. Some prototypes were created to benchmark possible solutions.

- Contact: Damien Caselli
- URL: https://github.com/poppy-project/poppy-simu

6.1.8. PyPot

SCIENTIFIC DESCRIPTION

Pypot is a framework developed to make it easy and fast to control custom robots based on Dynamixel motors. This framework provides different levels of abstraction corresponding to different types of use. Pypot can be used to:

- control Robotis motors through a USB2serial device,
- define the structure of a custom robot and control it through high-level commands,
- define primitives and easily combine them to create complex behavior.

Pypot is part of the Poppy project. It is the core library used by the Poppy robots. This abstraction layer allows to seamlessly switch from a given Poppy robot to another. It also provides a common set of tools, such as forward and inverse kinematics, simple computer vision, recording and replaying moves, or easy access to the autonomous exploration library Explauto.

To extend pypot application domains and connection to outside world, it also provides an HTTP API. On top of providing an easy way to connect to smart sensors or connected devices, it is notably used to connect to Snap!, a variant of the well-known Scratch visual programming language.

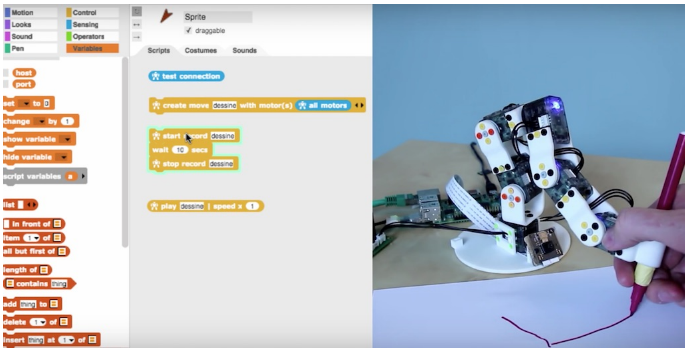

Figure 3. Example of using pypot to program a robot to reproduce a drawn shape

FUNCTIONAL DESCRIPTION

Pypot is entirely written in Python to allow for fast development, easy deployment and quick scripting by non-expert developers. It can also benefit from the scientific and machine learning libraries existing in Python. The serial communication is handled through the standard library and offers high performance (10ms sensorimotor loop) for common Poppy uses. It is cross-platform and has been tested on Linux, Windows and Mac OS.

Pypot is also compatible with the V-REP simulator. This allows the transparent switch from a real robot to its simulated equivalent with a single code base.

Finally, it has been developed to be easily and quickly extended for other types of motors and sensors.

It works with Python 2.7 or Python 3.3 or later, and has also been adapted to the Raspberry Pi board.

Pypot has been connected to Snap!, a variant of the famous Scratch visual language, developed to teach computer science to children. It is based on a drag-and-drop blocks interface to write scripts by assembling those blocks.

Thanks to the Snap! HTTP block, a connection can be made to pypot allowing users to directly control robots through their visual interfaces. A set of dedicated Snap! blocks have been designed, such as *set motor position* or *get motor temperature*. Thanks to the Snap! HTTP block, users can control robots through this visual interfaces connecting to Pypot. A set of dedicated Snap! blocks has been designed, such as *set motor position* or *get motor temperature*.

Figure 4. Using Snap! to program a robot by demonstration and create complex choreographies

Snap! is also used as a tool to program the robot by demonstration. Using the *record* and *play* blocks, users can easily trigger kinesthetic recording of the whole robot or only a specific subpart, such as an arm. These records can then be played or "mixed" - either played in sequence or simultaneously - with other recordings to compose complex choreographies. The moves are encoded as a model of mixture of gaussians (GMM) which allows the definition of clean mathematical operators for combining them.

This recording tool has been developed and used in collaboration with artists who show interest in the concept of robotic moves.

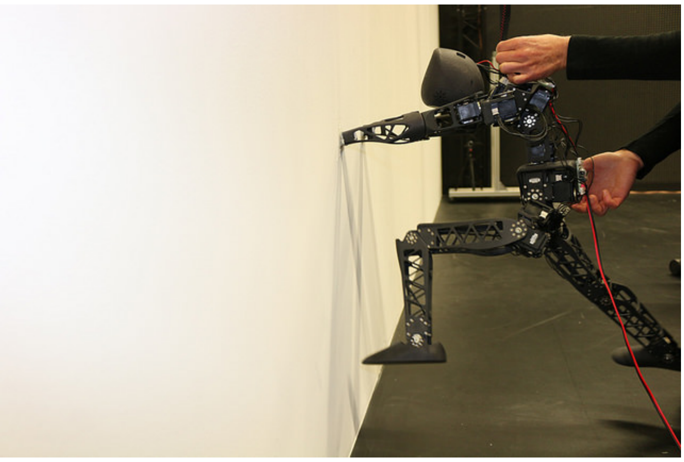

Figure 5. Artistic project exploring the concept of robotic move.

- Participants: Pierre Rouanet, Matthieu Lapeyre, Steve Nguyen, Damien Caselli and Theo Segonds
- Contact: Theo Segonds

- URL: https://github.com/poppy-project/pypot

6.1.9. PyQMC

Python library for Quasi-Metric Control

FUNCTIONAL DESCRIPTION

PyQMC is a python library implementing the control method described in http://dx.doi.org/10.1371/journal.pone.0083411 It allows to solve discrete markovian decision processes by computing a Quasi-Metric on the state space. This model based method has the advantage to be goal independant and thus can produce a policy for any goal with relatively few recomputation. New addition to this method is the possibility of online learning of the transition model and the Quasi-Metric.

- Participant: Steve Nguyen
- Contact: Steve Nguyen
- URL: https://github.com/SteveNguyen/pyqmc

6.2. Explauto

an autonomous exploration library

SCIENTIFIC DESCRIPTION

An important challenge in developmental robotics is how robots can be intrinsically motivated to learn efficiently parametrized policies to solve parametrized multi-task reinforcement learning problems, i.e. learn the mappings between the actions and the problem they solve, or sensory effects they produce. This can be a robot learning how arm movements make physical objects move, or how movements of a virtual vocal tract modulates vocalization sounds. The way the robot will collects its own sensorimotor experience have a strong impact on learning efficiency because for most robotic systems the involved spaces are high dimensional, the mapping between them is non-linear and redundant, and there is limited time allowed for learning. If robots explore the world in an unorganized manner, e.g. randomly, learning algorithms will be often ineffective because very sparse data points will be collected. Data are precious due to the high dimensionality and the limited time, whereas data are not equally useful due to non-linearity and redundancy. This is why learning has to be guided using efficient exploration strategies, allowing the robot to actively drive its own interaction with the environment in order to gather maximally informative data to optimize the parametrized policies. In the recent year, work in developmental learning has explored various families of algorithmic principles which allow the efficient guiding of learning and exploration.

Explauto is a framework developed to study, model and simulate curiosity-driven learning and exploration in real and simulated robotic agents. Explauto's scientific roots trace back from Intelligent Adaptive Curiosity algorithmic architecture [152], which has been extended to a more general family of autonomous exploration architectures by [3] and recently expressed as a compact and unified formalism [38]. The library is detailed in [39]. In Explauto, interest models are implementing the strategies of active selection of particular problems / goals in a parametrized multi-task reinforcement learning setup to efficiently learn parametrized policies. The agent can have different available strategies, parametrized problems, models, sources of information, or learning mechanisms (for instance imitate by mimicking vs by emulation, or asking help to one teacher or to another), and chooses between them in order to optimize learning (a processus called strategic learning [45]). Given a set of parametrized problems, a particular exploration strategy is to randomly draw goals/ RL problems to solve in the motor or problem space. More efficient strategies are based on the active choice of learning experiments that maximize learning progress using bandit algorithms, e.g. maximizing improvement of predictions or of competences to solve RL problems [152]. This automatically drives the system to explore and learn first easy skills, and then explore skills of progressively increasing complexity. Both random and learning progress strategies can act either on the motor or on the problem space, resulting in motor babbling or goal babbling strategies.

- Motor babbling consists in sampling commands in the motor space according to a given strategy (random or learning progress), predicting the expected effect, executing the command through the environment and observing the actual effect. Both the parametrized policies and interest models are finally updated according to this experience.
- Goal babbling consists in sampling goals in the problem space and to use the current policies to infer a motor action supposed to solve the problem (inverse prediction). The robot/agent then executes the command through the environment and observes the actual effect. Both the parametrized policies and interest models are finally updated according to this experience.It has been shown that this second strategy allows a progressive solving of problems much more uniformly in the problem space than with a motor babbling strategy, where the agent samples directly in the motor space [3].

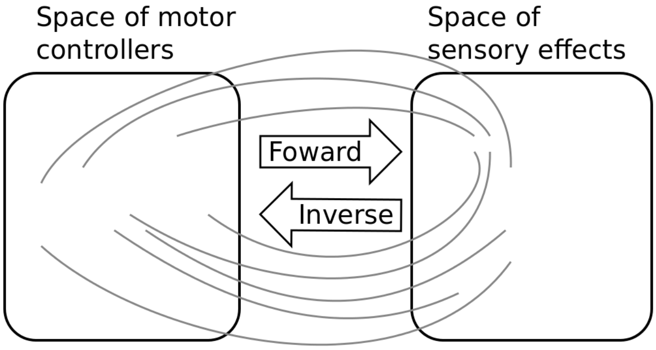

Figure 6. Complex parametrized policies involve high dimensional action and effect spaces. For the sake of visualization, the motor M and sensory S spaces are only 2D each in this example. The relationship between M and S is non-linear, dividing the sensorimotor space into regions of unequal stability: small regions of S can be reached very precisely by large regions of M, or large regions in S can be very sensitive to variations in M.: s as well as a non-linear and redundant relationship. This non-linearity can imply redundancy, where the same sensory effect can be attained using distinct regions in M.

FUNCTIONAL DESCRIPTION

This library provides high-level API for an easy definition of:

- Real and simulated robotic setups (Environment level),
- Incremental learning of parametrized policies (Sensorimotor level),
- Active selection of parametrized RL problems (Interest level).

The library comes with several built-in environments. Two of them corresponds to simulated environments: a multi-DoF arm acting on a 2D plan, and an under-actuated torque-controlled pendulum. The third one allows to control real robots based on Dynamixel actuators using the Pypot library. Learning parametrized policies involves machine learning algorithms, which are typically regression algorithms to learn forward models, from motor controllers to sensory effects, and optimization algorithms to learn inverse models, from sensory effects, or problems, to the motor programs allowing to reach them. We call these sensorimotor learning algorithms sensorimotor models. The library comes with several built-in sensorimotor models: simple nearest-neighbor look-up, non-parametric models combining classical regressions and optimization algorithms, online mixtures of Gaussians, and discrete Lidstone distributions. Explauto sensorimotor models are online learning algorithms, i.e. they are trained iteratively during the interaction of the robot in theenvironment in which it evolves. Explauto provides also a unified interface to define exploration strategies using the InterestModel class. The library comes with two built-in interest models: random sampling as well as sampling maximizing the learning progress in forward or inverse predictions.

Explauto environments now handle actions depending on a current context, as for instance in an environment where a robotic arm is trying to catch a ball: the arm trajectories will depend on the current position of the ball (context). Also, if the dynamic of the environment is changing over time, a new sensorimotor model (Non-Stationary Nearest Neighbor) is able to cope with those changes by taking more into account recent experiences. Those new features are explained in Jupyter notebooks.

This library has been used in many experiments including:

- the control of a 2D simulated arm,
- the exploration of the inverse kinematics of a poppy humanoid (both on the real robot and on the simulated version),
- acoustic model of a vocal tract.

Explauto is crossed-platform and has been tested on Linux, Windows and Mac OS. It has been released under the GPLv3 license.

- Contact: Sébastien Forestier
- URL: https://github.com/flowersteam/explauto

6.3. Tools for robot learning, control and perception

6.3.1. CARROMAN

FUNCTIONAL DESCRIPTION

This software implements a control architecture for the Meka humanoid robot. It integrates the Stanford Whole Body Control in the M3 architecture provided with the Meka robot, and provides clear and easy to use interfaces through the URBI scripting language. This software provides a modular library of control modes and basic skills for manipulating objects, detecting objects and humans which other research projects can reuse, extend and enhance. An example would be to locate a cylindrical object on a table using stereo vision, and grasping it using position and force control.

- Contact: David Filliat

6.3.2. Aversive++

FUNCTIONAL DESCRIPTION

Aversive++ is a C++ library that eases micro-controller programming. Its aim is to provide an interface simple enough to be able to create complex applications, and optimized enough to enable small micro-controllers to execute these applications. The other aspect of this library is to be multiplatform. Indeed, it is designed to provide the same API for a simulator (named SASIAE) and for AVR-based and ARM-based micro-controllers.

- Contact: Loïc Dauphin
- URL: http://aversiveplusplus.com/

6.3.3. DMP-BBO

Black-Box Optimization for Dynamic Movement Primitives
KEYWORD: -
FUNCTIONAL DESCRIPTION

The DMP-BBO Matlab library is a direct consequence of the insight that black-box optimization outperforms reinforcement learning when using policies represented as Dynamic Movement Primitives. It implements several variants of the PIBB algorithm for direct policy search. The dmp-bbo C++ library has been extended to include the “unified model for regression”. The implementation of several of the function approximators have been made real-time compatible.

- Participant: Freek Stulp
- Partner: ENSTA
- Contact: Freek Stulp
- URL: https://github.com/stulp/dmpbbo

6.3.4. KERAS-QR

KERAS with Quick Reset

KEYWORDS: Library - Deep learning

- Participant: Florian Golemo
- Contact: Florian Golemo
- URL: https://github.com/fgolemo/keras

6.3.5. Multimodal

FUNCTIONAL DESCRIPTION

The python code provides a minimum set of tools and associated libraries to reproduce the experiments in [98] , together with the choreography datasets. The code is primarily intended for reproduction of the mulimodal learning experiment mentioned above. It has already been reused in several experimentations by other member of the team and is expected to play an important role in further collaborations. It is also expected that the public availability of the code encourages further experimentation by other scientists with data coming from other domains, thus increasing both the impact of the aforementioned publication and the knowledge on the algorithm behaviors.

- Participant: Olivier Mangin
- Contact: Olivier Mangin
- URL: https://github.com/omangin/multimodal

6.3.6. Of 3-D point cloud

FUNCTIONAL DESCRIPTION

This software scans the 3-D point cloud of a scene to find objects and match them against a database of known objects. The process consists in 3 stages. The segmentation step finds the objects in the point cloud, the feature extraction computes discriminating properties to be used in the classification stage for object recognition.

- Participants: David Filliat, Alexander Gepperth and Louis-Charles Caron
- Contact: Alexander Gepperth

6.3.7. PEDDETECT

FUNCTIONAL DESCRIPTION

PEDDETECT implements real-time person detection in indoor or outdoor environments. It can grab image data directly from one or several USB cameras, as well as from pre-recorded video streams. It detects mulitple persons in 800x600 color images at frame rates of >15Hz, depending on available GPU power. In addition, it also classifies the pose of detected persons in one of the four categories "seen from the front", "seen from the back", "facing left" and "facing right". The software makes use of advanced feature computation and nonlinear SVM techniques which are accelerated using the CUDA interface to GPU programming to achieve high frame rates. It was developed in the context of an ongoing collaboration with Honda Research Institute USA, Inc.

- Participant: Alexander Gepperth
- Contact: Alexander Gepperth

6.3.8. ThifloNet

KEYWORDS: Deep learning - Policy Learning
SCIENTIFIC DESCRIPTION

We created a software architecture that combines a state-of-the-art computer vision system with a policy learning framework. This system is able to perceive a visual scene, given by a still image, extract facts (“predicates”), and propose an optimal action to achieve a given goal. Both systems are chained into a pipeline that is trained by presenting images and demonstrating an optimal action. By providing this information, both the predicate recognition model and the policy learning model are updated.

Our architecture is based on the recent works of Lerer, A., Gross, S., & Fergus, R., 2016 ("Learning Physical Intuition of Block Towers by Example"). They created a large network able to identify physical properties of stacked blocks. Analogously our vision system utilizes the same network layout (without the image prediction auxiliary output), with an added output layer for predicates, based on the expected number and arity of predicates. The vision subsystem is not trained with a common cross-entropy or MSE loss function, but instead receives its loss form the policy learning subsystem. The policy learning module calculates the loss as optimal combination of predicates for the given expert action.

By using this combination of systems, the architecture as a whole requires significantly fewer data samples than other systems (which exclusively utilize neural networks). This makes the approach more feasible to real-life applciation with actual live demonstration.
FUNCTIONAL DESCRIPTION

The neural network consists of ResNet-50 (the currently best-performing computer vision system), with 50 layers, 2 layers for converting the output of ResNet to predicates and a varying amount of output neurons, corresponding to the estimated number of n-arity predicates. The network was pretrained on the ImageNet dataset. The policy learning module incorporates the ACE tree learning tool and a wrapper in Prolog.

Our example domain consists of 2-4 cubes colored in red, blue, green, and yellow and randomly stacked on top of each other in a virtual 3D environment. The dataset used for training and testing contains a total of 30000 elements, each with an image of the scene, the correct predicates, a list of blocks that are present and the corresponding expert action, that would lead to stacking the blocks to a tower.

- Participants: Florian Golemo, Thibaut Munzer and Manuel Lopes
- Contact: Florian Golemo

6.4. Tools for education

6.4.1. KidLearn

KEYWORD: Automatic Learning
FUNCTIONAL DESCRIPTION

KidLearn is a software which adaptively personalize sequences of learning activities to the particularities of each individual student. It aims at proposing to the student the right activity at the right time, maximizing concurrently his learning progress and its motivation. The library regrouping the different developed technologies is available on github.

- Participants: Benjamin Clement, Pierre Yves Oudeyer, Didier Roy and Manuel Lopes
- Contact: Manuel Lopes
- URL: https://flowers.inria.fr/research/kidlearn/, https://github.com/flowersteam/kidlearn

6.4.2. KidBreath

FUNCTIONAL DESCRIPTION

KidBreath is a web responsive application composed by several interactive contents linked to asthma and displayed to different forms: learning activities with quiz, short games and videos. There are profil creation and personalization, and a part which describes historic and scoring of learning activities, to see evolution of Kidreath use. To test Kidlearn algorithm, it is iadapted and integrated on this platform. Development in PHP, HTML-5, CSS, MySQL, JQuery, Javascript. Hosting in APACHE, LINUX, PHP 5.5, MySQL, OVH.

- Partner: ItWell SAS
- Contact: Alexandra Delmas
- URL: http://www.kidbreath.fr

6.4.3. Kidlearn: money game application

FUNCTIONAL DESCRIPTION

The games is instantiated in a browser environment where students are proposed exercises in the form of money/token games (see Figure 7). For an exercise type, one object is presented with a given tagged price and the learner has to choose which combination of bank notes, coins or abstract tokens need to be taken from the wallet to buy the object, with various constraints depending on exercises parameters. The games have been developed using web technologies, HTML5, javascript and Django.

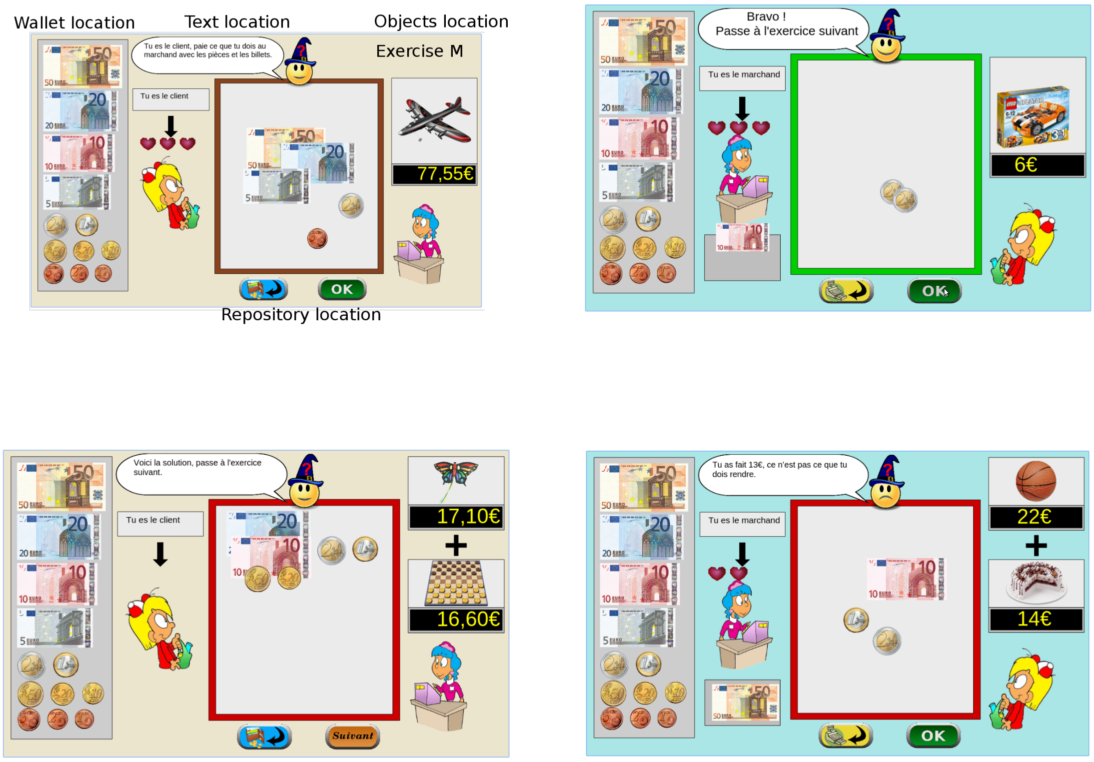

Figure 7. Four principal regions are defined in the graphical interface. The first is the wallet location where users can pick and drag the money items and drop them on the repository location to compose the correct price. The object and the price are present in the object location. Four different types of exercises exist: M : customer/one object, R : merchant/one object, MM : customer/two objects, RM : merchant/two objects.

- Contact: Benjamin Clement
- URL: https://flowers.inria.fr/research/kidlearn/

6.4.4. Kidlearn: script for Kidbreath use

FUNCTIONAL DESCRIPTION

A new way to test Kidlearn algorithms is to use them on Kidbreath Plateform. The Kidbreath Plateform use apache/PHP server, so to facilitate the integration of our algorithm, a python script have been made to allow PHP code to use easily the python library already made which include our algorithms.

Github link to explanation about it : https://github.com/flowersteam/kidlearn/tree/feature/kidbreath/module_php.

- Contact: Benjamin Clement
- URL: https://github.com/flowersteam/kidlearn/tree/feature/kidbreath/module_php

6.5. 3rdHand Project

6.5.1. 3rdHand Infrastructure

KEYWORDS: Interaction - Robotics - Infrastructure software - Framework - Robot Operating System (ROS)
FUNCTIONAL DESCRIPTION

The infrastructure is predicate-based to handle relational actions and covers perception (scene description generation, human actions recognition), decision making (teleoperated, scripted or learning from demonstrations), interaction with end users (GUI, voice, gestures) and parallel executions of robotic actions (hold, pick, grasp, bring, ...).

- Contact: Yoan Mollard
- https://github.com/3rdHand-project/thr_infrastructure

6.5.2. Kinect 2 Server

Kinect 2 server
KEYWORDS: Depth Perception - Speech recognition - Gesture recognition - Kinect
FUNCTIONAL DESCRIPTION

The server written in C# uses the Kinect SDK v2 to get the RGBD raw image, skeleton tracking information, recognized speech. It also uses the text-to-speech from Microsoft. Then it streams JSON data over the network using the Publisher/Subscriber pattern from the ZeroMQ network library. A Linux client has been written in Python but it can be written in any other language that is compatible with ZeroMQ. Features are controllable through a Graphical User Interface on Windows, or through the code from any Linux/Windows client. The clients can for instance enable features (speech recognition on, skeleton tracking off, . . .) and parameters (set new speech to recognize, change language, . . .) from remote.

- Contact: Yoan Mollard
- URL: https://github.com/baxter-flowers/kinect_2_server/

6.5.3. ProMP

Probabilistic Movement Primitives
KEYWORDS: Interaction - Robotics - Probability - Motion model - Robot Operating System (ROS)
FUNCTIONAL DESCRIPTION

Joint-space primitives with a task-space constraint: The primitives are stored in joint-space but demonstrations are provided both in joint space and task space, context. Thanks to this context, task-space goals can be requested to these joint-space primitives. The benefit is that requesting a new task-space goal does not require to call an IK method which would return demonstrations-agnostic joint configurations.

Vocal interactive learning and clustering: This work includes an interactive learning aspect which allows to automatically cluster motor primitives based on the standard deviation of their demonstrations. A new primitive is created automatically if the provided demonstration is out of 2 standard deviation of the existing primitives, otherwise the demonstration is distributed to an existing one.

- Contact: Yoan Mollard
- URL: https://github.com/baxter-flowers/promplib

6.5.4. ROS Optitrack Publisher

KEYWORDS: Target tracking - Robot Operating System (ROS)
FUNCTIONAL DESCRIPTION

This package allows to publish optitrack markers declared as rigid bodies as TF transforms. Data is gathered through the embedded VRPN server of Motive/Arena. Only rigid bodies are requested to the server, thus single points in 2D/3D are ignored. VRPN server can be enable in View > Data streaming in Motive.

- Contact: Yoan Mollard
- URL: https://github.com/baxter-flowers/optitrack_publisher

7. New Results

7.1. Robotic And Computational Models Of Human Development and Cognition

7.1.1. Computational Models Of Information-Seeking, Curiosity And Attention in Humans and Animals

Participants: Manuel Lopes, Pierre-Yves Oudeyer [correspondant], Jacqueline Gottlieb, Celeste Kidd, Alvaro Ovalle, William Schueller, Sebastien Forestier, Nabil Daddaouda, Nicholas Foley.

This project involves a collaboration between the Flowers team, the Cognitive Neuroscience Lab of J. Gottlieb at Columbia Univ. (NY, US), and the developmental psychology lab of Celeste Kidd at Univ. Rochester, US, on the understanding and modeling of mechanisms of curiosity, attention and active intrinsically motivated exploration that until now have been little explored in neuroscience, machine learning and cognitive robotics.

It is organized around the study of the hypothesis that information gain (or control gain) could generate intrinsic reward in the brain (living or artificial), driving attention and exploration independently from material rewards, and allowing for autonomous lifelong acquisition of open repertoires of skills. The project combines expertise about attention and exploration in the brain and a strong methodological framework for conducting experimentations with monkeys, human adults (Gottlieb's lab) and children (Kidd's lab) together with computational modeling of curiosity/intrinsic motivation and learning in the Flowers team.

Such a collaboration paves the way towards a central objective, which is now a central strategic objective of the Flowers team: designing and conducting experiments in animals and humans informed by computational/mathematical theories of information seeking, and allowing to test the predictions of these computational theories.

7.1.1.1. Context

Curiosity can be understood as a family of mechanisms that evolved to allow agents to maximize their knowledge (or their control) of the useful properties of the world - i.e., the regularities that exist in the world - using active, targeted investigations. In other words, we view curiosity as a decision process that maximizes learning/competence progress (rather than minimizing uncertainty) and assigns value ("interest") to competing tasks based on their epistemic qualities - i.e., their estimated potential allow discovery and learning about the structure of the world.

Because a curiosity-based system acts in conditions of extreme uncertainty (when the distributions of events may be entirely unknown) there is in general no optimal solution to the question of which exploratory action to take [29], [155], [162]. Therefore we hypothesize that, rather than using a single optimization process as it has been the case in most previous theoretical work [131], curiosity is comprised of a family of mechanisms that include simple heuristics related to novelty/surprise and measures of learning progress over longer time scales [153] [110], [149]. These different components are related to the subject's epistemic state (knowledge and beliefs) and may be integrated with fluctuating weights that vary according to the task context. We will quantitatively characterize this dynamic, multi-dimensional system in the framework of Bayesian Reinforcement Learning, as described below.

Because of its reliance on epistemic currencies, curiosity is also very likely to be sensitive to individual differences in personality and cognitive functions. Humans show well-documented individual differences in curiosity and exploratory drives [143], [161], and rats show individual variation in learning styles and novelty seeking behaviors [128], but the basis of these differences is not understood. We postulate that an important component of this variation is related to differences in working memory capacity and executive control which, by affecting the encoding and retention of information, will impact the individual's assessment of learning, novelty and surprise and ultimately, the value they place on these factors [159], [171], [106], [175]. To start understanding these relationships, about which nothing is known, we will search for correlations between curiosity and measures of working memory and executive control in the population of children we test in our tasks, analyzed from the point of view of a computational model based on Bayesian reinforcement learning.

A final premise guiding our research is that essential elements of curiosity are shared by humans and non-human primates. Human beings have a superior capacity for abstract reasoning and building causal models, which is a prerequisite for sophisticated forms of curiosity such as scientific research. However, if the task is adequately simplified, essential elements of curiosity are also found in monkeys [143], [141] and, with adequate characterization, this species can become a useful model system for understanding the neurophysiological mechanisms.

7.1.1.2. Objectives

Our studies have several highly innovative aspects, both with respect to curiosity and to the traditional research field of each member team.

- Linking curiosity with quantitative theories of learning and decision making: While existing investigations examined curiosity in qualitative, descriptive terms, here we propose a novel approach that integrates quantitative behavioral and neuronal measures with computationally defined theories of Bayesian Reinforcement Learning and decision making.
- Linking curiosity in children and monkeys: While existing investigations examined curiosity in humans, here we propose a novel line of research that coordinates its study in humans and non-human primates. This will address key open questions about differences in curiosity between species, and allow access to its cellular mechanisms.
- Neurophysiology of intrinsic motivation: Whereas virtually all the animal studies of learning and decision making focus on operant tasks (where behavior is shaped by experimenter-determined primary rewards) our studies are among the very first to examine behaviors that are intrinsically motivated by the animals' own learning, beliefs or expectations.
- Neurophysiology of learning and attention: While multiple experiments have explored the single-neuron basis of visual attention in monkeys, all of these studies focused on vision and eye movement control. Our studies are the first to examine the links between attention and learning, which are recognized in psychophysical studies but have been neglected in physiological investigations.
- Computer science: biological basis for artificial exploration: While computer science has proposed and tested many algorithms that can guide intrinsically motivated exploration, our studies are the first to test the biological plausibility of these algorithms.
- Developmental psychology: linking curiosity with development: While it has long been appreciated that children learn selectively from some sources but not others, there has been no systematic investigation of the factors that engender curiosity, or how they depend on cognitive traits.

7.1.1.3. Current results

In particular, new results in 2015 include:

7.1.1.4. Intrinsically motivated oculomotor exploration guided by uncertainty reduction and conditioned reinforcement in non-human primates

Using a novel oculomotor paradigm, combined with reinforcement learning (RL) simulations, we show that monkeys are intrinsically motivated to search for and look at reward-predictive cues, and that their intrinsic motivation is shaped by a desire to reduce uncertainty, a desire to obtain conditioned reinforcement from positive cues, and individual variations in decision strategy and the cognitive costs of acquiring information. The results suggest that free-viewing oculomotor behavior reveals cognitive and emotional factors underlying the curiosity driven sampling of information. These results were published in [66].

7.1.1.5. Experiments in Active Categorization

An ongoing effort to characterize curiosity and exploration in an experimental setting consists in evaluating the manner in which diverse tasks or goals are selected. This would include monitoring what does a test subject decide to learn, in what order and how is it done. This has been referred to as strategic learning [31]. Accordingly, it is of particular interest for the project to observe the type of learning dynamics in relation to their learning progress [153]. This principle tries to establish links between the selection and ordering of tasks and the speed or the rate of improvement a subject may achieve. This implies that during free exploration the subject would focus on tasks that are considered of certain complexity and where it makes consistent progress. At the same time the subject would avoid: (1) trivial tasks that do not offer much learning due to their simplicity or (2) very complicated tasks where little or no progress is achieved.

We have been working on prototyping an experiment where the subject is presented with different stimuli classification tasks of varying difficulty. The goal for each of the tasks is to correctly predict and differentiate between different classes of stimuli. Two main aspects of the task are under the control of the subject: (1) the task that he/she wants to learn and (2) once selected a task, what elements to explore in order to subsequently being able to predict future stimuli. Essentially the subject autonomously organizes which tasks to focus on and in what order. Therefore one of the objectives of this investigation is to analyze if the learning dynamics are guided by the amount of progress the subject achieves in the tasks.

7.1.2. Computational Models Of Tool Use and Speech Development: the Roles of Active Learning, Curiosity and Self-Organization

Participants: Pierre-Yves Oudeyer [correspondant], Clement Moulin-Frier, Sébastien Forestier, Linda Smith.

7.1.2.1. Modeling Cognitive Development and Tool Use in Infants

A scientific challenge in developmental and social robotics is to model how autonomous organisms can develop and learn open repertoires of skills in high-dimensional sensorimotor spaces, given limited resources of time and energy. This challenge is important both from the fundamental and application perspectives. First, recent work in robotic modeling of development has shown that it could make decisive contributions to improve our understanding of development in human children, within cognitive sciences [131]. Second, these models are key for enabling future robots to learn new skills through lifelong natural interaction with human users, for example in assistive robotics [157].

In recent years, two strands of work have shown significant advances in the scientific community. On the one hand, algorithmic models of active learning and imitation learning combined with adequately designed properties of robotic bodies have allowed robots to learn how to control an initially unknown high-dimensional body (for example locomotion with a soft material body [3]). On the other hand, other algorithmic models have shown how several social learning mechanisms could allow robots to acquire elements of speech and language [118], allowing them to interact with humans. Yet, these two strands of models have so far mostly remained disconnected, where models of sensorimotor learning were too “low-level” to reach capabilities for language, and models of language acquisition assumed strong language specific machinery limiting their flexibility. Preliminary work has been showing that strong connections are underlying mechanisms of hierarchical sensorimotor learning, artificial curiosity, and language acquisition [49].

Recent robotic modeling work in this direction has shown how mechanisms of active curiosity-driven learning could progressively self-organize developmental stages of increasing complexity in vocal skills sharing many properties with the vocal development of infants [37]. Interestingly, these mechanisms were shown to be exactly the same as those that can allow a robot to discover other parts of its body, and how to interact with external physical objects [152].

In such current models, the vocal agents do not associate sounds to meaning, and do not link vocal production to other forms of action. In other models of language acquisition, one assumes that vocal production is mastered, and hand code the meta-knowledge that sounds should be associated to referents or actions [118]. But understanding what kind of algorithmic mechanisms can explain the smooth transition between the learning of vocal sound production and their use as tools to affect the world is still largely an open question.

The goal of this work is to elaborate and study computational models of curiosity-driven learning that allow flexible learning of skill hierarchies, in particular for learning how to use tools and how to engage in social interaction, following those presented in [152],[3], [43], [37]. The aim is to make steps towards addressing the fundamental question of how speech communication is acquired through embodied interaction, and how it is linked to tool discovery and learning.

A first question that we study in this work is the type of mechanisms that could be used for hierarchical skill learning allowing to manage new task spaces and new action spaces, where the action and task spaces initially given to the robot are continuous and high-dimensional and can be encapsulated as primitive actions to affect newly learnt task spaces.

We presented firsts results on that question at the 38th Annual Meeting of the Cognitive Science Society, Philadelphia, Pennsylvania, USA, August 10-13th [80]. In this work, we presented the HACOB (Hierarchical Active Curiosity-driven mOdel Babbling) architecture of algorithms that actively chooses which sensorimotor model to train in a hierarchy of models representing the environmental structure. We studied this architecture using a simulated robotic arm interacting with objects in a 2D environment (See Fig. 8). Studies of child development of tool use precursors showed successive but overlapping phases of qualitatively different types of behaviours [167]. We hypothesized that two mechanisms in particular play a role in the structuring of these phases: the intrinsic motivation to explore and the representation used to encode sensorimotor experience.

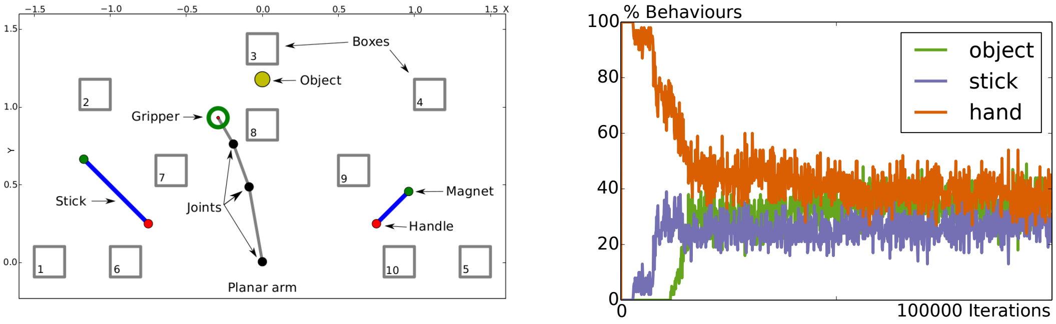

Figure 8. Left: simulated robotic environment with a 4 DOF robotic arm, 2 tools and a toy. Right: Observed behaviours of an agent: it first explores its arm to move its hand, then also explore to move the stick and the toy.

We showed that using a hierarchical structure of sensorimotor models and active model babbling as an intrinsic motivation to explore sensorimotor models that have a high learning progress, then overlapping phases of behaviours are autonomously emerging in the developmental trajectories of agents. To our knowledge, this is the first model of curiosity-driven development of simple tool use and of the self-organization of overlapping phases of behaviours. In particular, our model explains why and how intrinsically motivated exploration of non-optimal methods to solve certain sensorimotor problems can be useful to discover how to solve other sensorimotor problems, in accordance with Siegler's overlapping waves theory, by scaffolding the learning of increasingly complex affordances in the environment.

In computational models of strategy selection for the problem of integer addition, Shrager and Siegler proposed a mechanism that maintains the concurrent exploration of alternative strategies with use frequencies that are proportional to their performance for solving a particular problem. This mechanism was also used by Chen and Siegler to interpret an experiment with 1.5- and 2.5-year-olds that had to retrieve an out-of-reach toy, and where they could use one of several available strategies that included leaning forward to grasp a toy with the hand or using a tool to retrieve the toy.

In a paper that we presented at the The Sixth Joint IEEE International Conference on Developmental Learning and Epigenetic Robotics, Cergy-Pontoise, France, September 19-22nd [82], we studied tool use discovery and considered other mechanisms of strategy selection and evaluation. In particular, we presented models of curiosity-driven exploration where strategies are explored according to the learning progress/information gain they provide (as opposed to their current efficiency to actually solve the problem). In these models, we defined a curiosity-driven agent learning a hierarchy of different sensorimotor models in a simple 2D setup with a robotic arm, a stick and a toy. In a first phase, the agent learns from scratch how to use its robotic arm to control the tool and to catch the toy, and in a second phase with the same learning mechanisms, the agent has to solve three problems where the toy can only be reached with the tool (See Fig. 9). We showed that agents choosing strategies based on learning progress also display overlapping waves of behavior compatible with the one observed in infants, and we suggested that curiosity-driven exploration could be at play in Chen and Siegler's experiment, and more generally in tool use discovery.

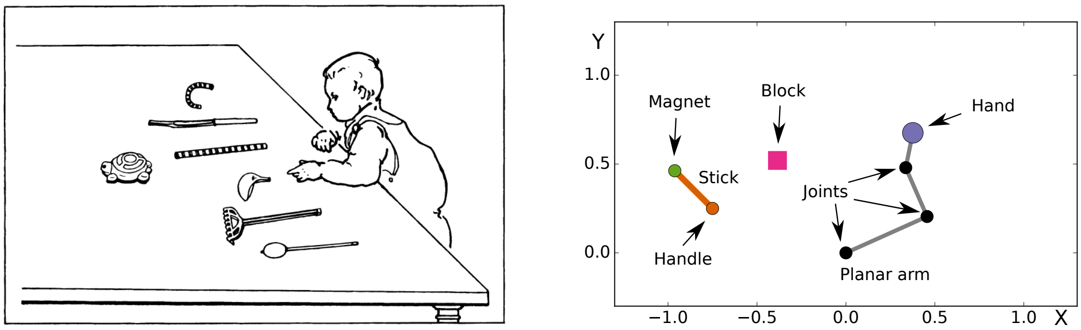

Figure 9. Left: Chen and Siegler's experimental setup with 1.5 and 2.5 years old babies who have to pick the good toy to retrieve an interesting toy. Right: Simulated robotic setup with a 3 DOF robotic arm that has 2 strategies to retrieve a toy: either grasp it with the hand, or use the stick to pull the toy.

7.1.2.2. Curiosity-driven developmental processes and their role in development and evolution of language

Infants' own activities create and actively select their learning experiences. In a collaboration with Linda Smith, we have analyzed recent models of embodied information seeking and curiosity-driven learning and have showed that these mechanisms have deep implications for development and evolution. In [69], we have discussed how these mechanisms yield self-organized epigenesis with emergent ordered behavioral and cognitive developmental stages. We described a robotic experiment that explored the hypothesis that progress in learning, in and for itself, generates intrinsic rewards: the robot learners probabilistically selected experiences according to their potential for reducing uncertainty. In these experiments, curiosity-driven learning led the robot learner to successively discover object affordances and vocal interaction with its peers. We explain how a learning curriculum adapted to the current constraints of the learning system automatically formed, constraining learning and shaping the developmental trajectory. The observed trajectories in the robot experiment share many properties with those in infant development, including a mixture of regularities and diversities in the developmental patterns. Finally, we argued that such emergent developmental structures can guide and constrain evolution, in particular with regards to the origins of language.

7.1.3. Computational Models Of Developmental Exploration Mechanisms in Vocal Babbling and Arm Reaching in Infants

Participants: Pierre-Yves Oudeyer [correspondant], Clement Moulin-Frier, Freek Stulp, Jules Borchard.

7.1.3.1. Proximodistal Freeing of DOFs in Motor Learning as an Emergent Property of Stochastic Optimization Principles

To harness the complexity of their high-dimensional bodies during sensorimotor development, infants are guided by patterns of freezing and freeing of degrees of freedom. We have formulated and studied computationally the hypothesis that such patterns, such as the proximodistal freeing of degrees of freedom when learning to reach, can emerge spontaneously as the result of a family of stochastic optimization processes, without an innate encoding of a mat- urational schedule. In particular, we present simulated experiments with a 6-DOF arm where a computational learner progressively acquires reaching skills through adaptive exploration, and we show that a proximodistal organization appears spontaneously, which we denote PDFF (ProximoDistal Freezing and Freeing of degrees of freedom). We also compare the emergent structuration as different arm structures are used – from human-like to quite unnatural ones – to study the effect of different kinematic structures on the emergence of PDFF.

7.1.3.2. Emergent Jaw Predominance in Vocal Development through Stochastic Optimization

Infant vocal babbling is strongly relying on jaw oscillations, especially at the stage of canonical babbling, which underlies the syllabic structure of world languages. We have proposed, modelled and analyzed an hypothesis to explain this predominance of the jaw in early babbling. This hypothesis states that general stochastic optimization principles, when applied to learning sensorimotor control, automatically generate ordered babbling stages with a predominant exploration of jaw movements in early stages, just like they generate proximo-distal organization of exploration in arm reaching as described in the paragraph above. In particular, such stochastic optimization principles predominantly explore jaw movement at the beginning of vocal learning, and when close to the rest position of the vocal tract, as it impacts the auditory effects more than other articulators.

7.1.4. Learning and Teaching in Adult-Child and Human-Robot Interaction

Participants: Anna-Lisa Vollmer [correspondant], Pierre-Yves Oudeyer.

7.1.4.1. Pragmatic Frames

One of the big challenges in robotics today is to learn from human users that are inexperienced in interacting with robots but yet are often used to teach skills flexibly to other humans and to children in particular. A potential route toward natural and efficient learning and teaching in Human-Robot Interaction (HRI) is to leverage the social competences of humans and the underlying interactional mechanisms. In this perspective, we propose 'pragmatic frames' as flexible interaction protocols that provide important contextual cues to enable learners to infer new action or language skills and teachers to convey these cues. Following the concept developed in the field of developmental linguistics [117], we define a pragmatic frame to be an interaction protocol negotiated over time between interaction partners. We further specify a Pragmatic Frame to especially involve an observable **coordinated sequence of behaviors** and also relevant **cognitive operations**.
Figure 10 depicts the book reading frame Bruner observed in his studies on word learning.

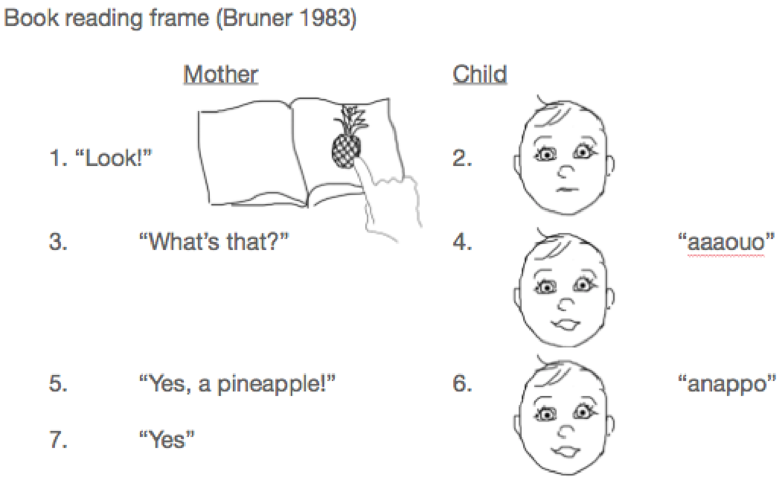

Figure 10. Example of a learning/teaching pragmatic frame.

At home, a mother is sitting on the sofa with her child on her lap and she is holding a picture book in front of them. The mother points to the book and says "look!" to direct the child's attention. The child then gazes to the image. And the mother asks "What's that?", prompting the child's performance. The child answers with babble strings and smiles, maybe "auo". "Yes, a pineapple!" The mother gives positive feedback and the correct label. "Anappo", again babble strings and smiles. And the mother gives positive feedback. This stable sequence that the child is familiar with helps the child to participate and to pick up the only variable information he or she is supposed to learn. We argue that this frame also triggers the relevant cognitive functions to process the information.

Our results in 2016 have been twofold. First, in a paper published in Frontiers in Psychology [70], we have given a theoretical account of pragmatic frames as an alternative to the mapping metaphor which posits that children learn a word by mapping it onto a concept of an object or event. However, we believe that a mapping metaphor cannot account for word learning, because even though children focus attention on objects, they do not necessarily remember the connection between the word and the referent unless it is framed pragmatically, that is, within a task. Word learning with pragmatic frames occurs as children accomplish a goal in cooperation with a partner. We elaborate on pragmatic frames, offer some initial parametrizations of the concept, and embed it in current language learning approaches.

Second, aiming at leveraging the concept of pragmatic frames for Human-Robot Interaction, we published an article in Frontiers in Neurorobotics [71] in which we study a selection of HRI work in the literature which has focused on learning–teaching interaction and analyze the interactional and learning mechanisms that were used in the light of pragmatic frames. This allows us to show that many of the works have already used in practice, but not always explicitly, basic elements of the pragmatic frames machinery. However, we also show that pragmatic frames have so far been used in a very restricted way as compared to how they are used in human–human interaction and argue that this has been an obstacle preventing robust natural multi-task learning and teaching in HRI. In particular, we explain that two central features of human pragmatic frames, mostly absent of existing HRI studies, are that (1) social peers use rich repertoires of frames, potentially combined together, to convey and infer multiple kinds of cues; (2) new frames can be learnt continually, building on existing ones, and guiding the interaction toward higher levels of complexity and expressivity. To conclude, we give an outlook on the future research direction describing the relevant key challenges that need to be solved for leveraging pragmatic frames for robot learning and teaching.

7.1.5. Models of Self-organization of lexical conventions: the role of Active Learning and Active Teaching in Naming Games

Participants: William Schueller [correspondant], Pierre-Yves Oudeyer.

How does language emerge, evolve and gets transmitted between individuals? What mechanisms underlie the formation and evolution of linguistic conventions, and what are their dynamics? Computational linguistic studies have shown that local interactions within groups of individuals (e.g. humans or robots) can lead to self-organization of lexica associating semantic categories to words [168]. However, it still doesn't scale well to complex meaning spaces and a large number of possible word-meaning associations (or lexical conventions), suggesting high competition among those conventions.

In statistical machine learning and in developmental sciences, it has been argued that an active control of the complexity of learning situations can have a significant impact on the global dynamics of the learning process [30], [131], [140]. This approach has been mostly studied for single robotic agents learning sensorimotor affordances [153], [38]. However active learning might represent an evolutionary advantage for language formation at the population level as well [49], [170].

Naming Games are a computational framework, elaborated to simulate the self-organization of lexical conventions in the form of a multi-agent model [169]. Through repeated local interactions between random couples of agents (designated *speaker* and *hearer*), shared conventions emerge. Interactions consist of uttering a word – or an abstract signal – referring to a topic, and evaluating the success or failure of communication.

However, in existing works processes involved in these interactions are typically random choices, especially the choice of a communication topic.

The introduction of active learning algorithms in these models produces significant improvement of the convergence process towards a shared vocabulary, with the speaker [53], [46], [122] or the hearer [90] actively controlling vocabulary growth.

We study here how the convergence time and the maximum level of complexity scale with population size, for three different strategies (one with random topic choice and two with active topic choice) detailed in table 11.

Naive (random)	Success Threshold	Minimal counts
$m \leftarrow \text{random}(\mathcal{M})$	**if** $\text{mean}\left(\frac{succ(i)}{succ(i)+fail(i)}\right)_{i\in\mathcal{LM}} \geq \boldsymbol{\alpha}$: $m \leftarrow \text{random}(\mathcal{UM})$ **else**: $m \leftarrow \text{argmin}_{i\in\mathcal{LM}}\left(\frac{succ(i)}{succ(i)+fail(i)}\right)$	**if** $\forall i \in \mathcal{LM}\ succ(i) > \boldsymbol{n}$: $m \leftarrow \text{random}(\mathcal{UM})$ **else**: $m \leftarrow \text{argmin}_{i\in\mathcal{LM}}(succ(i))$
$\mathcal{M}$: all meanings, $\mathcal{LM}$: labeled meanings, $\mathcal{UM}$: unlabeled meanings, μ: vocabulary size (# word-meaning associations) $succ$: # successful interactions per meaning, $fail$: # failed interactions per meaning		

Figure 11. Strategies: Choice of meaning m. Both active strategies use a parameter (α and n), which is each time chosen optimal in our simulations.

As for the version of the Naming Game used in our work, the scenario of the interaction is described in [90]. Vocabulary is updated as described in the Minimal Naming Game, detailed in [177]. In our simulations, we choose to set $N = M = W$, where N is the population size, M the number of meanings, and W the number of possible words. The computed theoretical success ratio of communication is used to represent the degree of convergence toward a shared lexicon for the whole population. A value of 1 means that the population reached full convergence. Complexity level of an individual lexicon is measured as the total number of distinct associations between meanings and words in the lexicon, or in other words: memory usage.

We show here (see figures 12,13) that convergence time and maximum complexity are reduced with active topic choice, a behavior that is amplified as larger populations are considered. The minimal counts strategy yields a strictly minimum complexity (equal to the complexity of a completed lexicon), while converging as

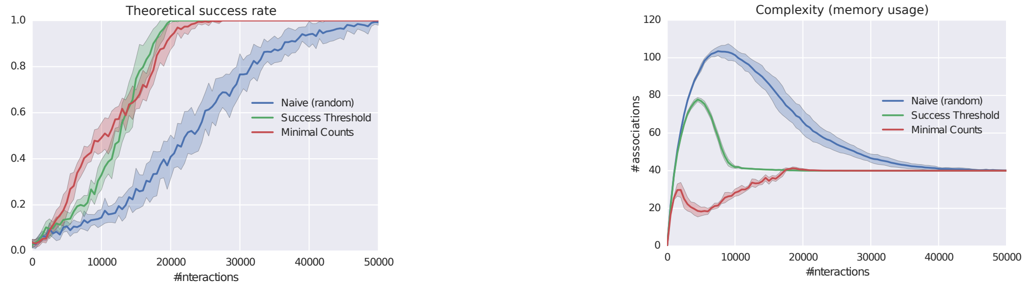

Figure 12. Strategy comparisons, in terms of convergence time (theoretical success ratio) and complexity level (memory usage). In this case, the hearer is the one choosing the topic. M=W=N=40, averaged over 8 trials

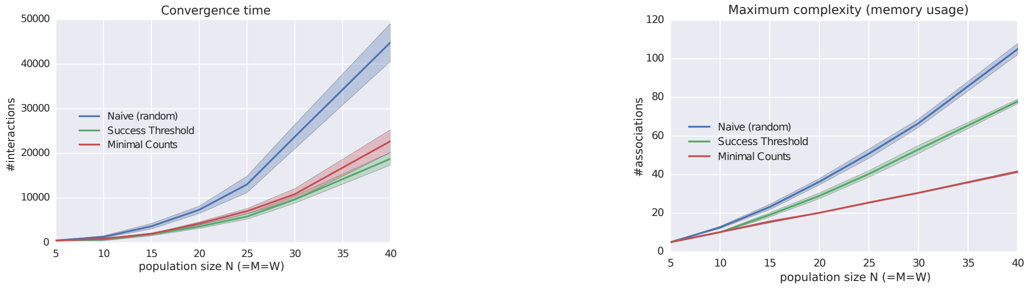

Figure 13. Scaling of maximum memory usage and convergence time for the different strategy, in function of population size. In this case, the hearer is the one choosing the topic. M=W=N, averaged over 8 trials.

fast as the success threshold strategy. Further work will deal with other variants of the Naming Game (with different vocabulary update, population replacement, and different ratio for N, M and W). For the moment only the hearer's choice scenario is studied, because of its high robustness to changes in parameter values for the different strategies [90].

7.2. Lifelong Robot Learning And Development Of Motor And Social Skills

7.2.1. Intrinsically Motivated Multitask Reinforcement Learning

Participants: Sébastien Forestier [correspondant], Pierre-Yves Oudeyer, Fabien Benureau.

7.2.1.1. Intrinsically Motivated Exploration of Spaces of Parameterized Skills/Tasks and Application to Robot Tool Learning

A major challenge in robotics is to learn parametrized policies to solve multi-task reinforcement learning problems in high-dimensional continuous action and effect spaces. Of particular interest is the acquisition of inverse models which map a space of sensorimotor problems to a space of motor programs that solve them. For example, this could be a robot learning which movements of the arm and hand can push or throw an object in each of several target locations, or which arm movements allow to produce which displacements of several objects potentially interacting with each other, e.g. in the case of tool use. Specifically, acquiring such repertoires of skills through incremental exploration of the environment has been argued to be a key target for life-long developmental learning [109].

In this work we study algorithms used by a learner to explore high-dimensional structured sensorimotor spaces such as in tool use discovery. We consider goal babbling architectures that were designed to explore and learn solutions to fields of sensorimotor problems, i.e. to acquire inverse models mapping a space of parameterized sensorimotor problems/effects to a corresponding space of parameterized motor primitives. However, so far these architectures have not been used in high-dimensional spaces of effects. Here, we show the limits of existing goal babbling architectures for efficient exploration in such spaces, and introduce a novel exploration architecture called Model Babbling (MB). MB exploits efficiently a modular representation of the space of parameterized problems/effects. We also study an active version of Model Babbling (the MACOB architecture). We compared those architectures in a simulated experimental setup with an arm that can discover and learn how to move objects using two tools with different properties, embedding structured high-dimensional continuous motor and sensory spaces (See Fig. 14).

7.2.1.2. Transfer Learning through Measures of Behavioral Diversity Generation in Autonomous Exploration

The production of behavioral diversity – producing a diversity of effects – is an essential strategy for robots exploring the world when facing situations where interaction possibilities are unknown or non-obvious. It allows to discover new aspects of the environment that cannot be inferred or deduced from available knowledge. However, creating behavioral diversity in situations where it is most crucial – new and unknown ones – is far from trivial. In particular in large and redundant sensorimotor spaces, only small areas are interesting to explore for any practical purpose. When the environment does not provide clues or gradient toward those areas, trying to discover those areas relies on chance. To address this problem, we introduce a method to create behavioral diversity in a new sensorimotor task by re-enacting actions that allowed to produce behavioral diversity in a previous task, along with a measure that quantifies this diversity. We have shownd that our method can learn how to interact with an object by reusing experience from another, that it adapts to instances of morphological changes and of dissimilarity between tasks, and how scaffolding behaviors can emerge by simply switching the attention of the robot to different parts of the environment. Finally, we show that the method can robustly use simulated experiences and crude cognitive models to generate behavioral diversity in real robots. This work was published in [62].

We presented the results at the IEEE/RSJ International Conference on Intelligent Robots and Systems, Daejeon, Korea, October 9-14th [81].

7.2.2. Social Learning of Interactive Skills

Participants: Manuel Lopes [correspondant], Thibaut Munzer, Marc Toussaint, Li Wang Wu, Yoan Mollard, Baptiste Busch, Jonathan Grizou, Marie Demangeat, Freek Stulp.

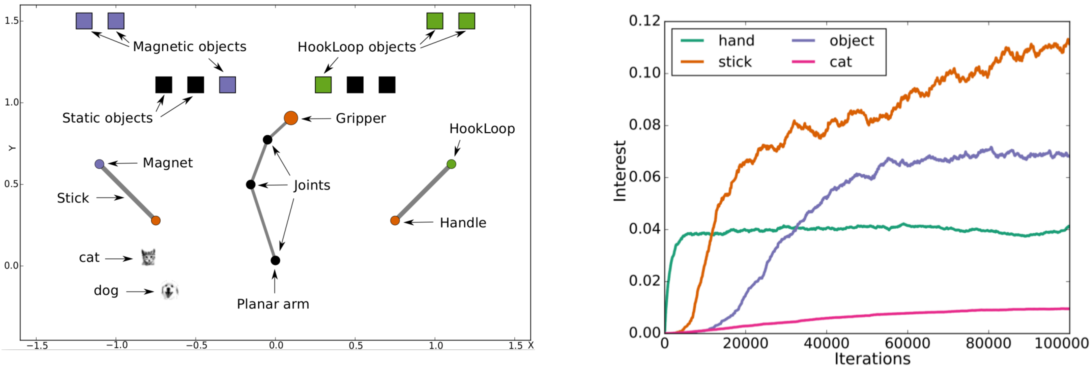

Figure 14. Left: Simulated robotic setup with a robotic arm that can grab tools to retrieve some interesting objects among a set of controllable and non-controllable (cat and dog) objects. Right: Evolution of the self-measured learning progress to move objects, with the MACOB active exploration architecture. The learning progress to explore objects is increasing for the tool and toy objects and stays low for the uncontrollable animals.

7.2.2.1. Relational Activity Processes for Modeling Concurrent Cooperation

In human-robot collaboration, multi-agent domains, or single-robot manipulation with multiple end-effectors, the activities of the involved parties are naturally concurrent. Such domains are also naturally relational as they involve objects, multiple agents, and models should generalize over objects and agents. We propose a novel formalization of relational concurrent activity processes that allows us to transfer methods from standard relational MDPs, such as MonteCarlo planning and learning from demonstration, to concurrent cooperation domains. We formally compare the formulation to previous propositional models of concurrent decision making and demonstrate planning and learning from demonstration methods on a real-world human-robot assembly task. A paper summarizing this research has been publish to the *International Conference on Robotics and Automation* (ICRA) 2016 [84].

7.2.2.2. Interactive Behavior Learning for Cooperative Tasks

This work goal is to propose a method to learn cooperative behavior to solve a task while performing the task with the user. The proposed approach reuses previous work on learning policy for RAP. The main differences are: i) formulate the problem as a cooperative process. In MDP and RAP, it is assumed that there is one central decision maker. However, in a cooperative both the robot and the operator are taking decisions. ii) estimating the confidence. A Query by Bagging approach has been used where many policies are learned from a subset of the data. Their potential disagreement allows quantifying the confidence. iii) Using the confidence for autonomous acting and for query making. Based on the confidence, the robot either act before acting or ask confirmation before acting.

Results show that using an interactive approach require less instruction from the user while producing a policy that makes fewer mistakes. We developed a robotic implementation 15 using a Baxter robot. A first article resulting from this work focusing on interactive preferences learning have been submitted to the *International Conference on Robotics and Automation* (ICRA) 2017 and a video demonstration can be view at : https://vimeo.com/182913540. A broader journal article is in preparation. We also conducted a user study to evaluate the impact of interactive learning on naïve users acceptation and performances.

7.2.2.3. Legible Motion

In a human-robot collaboration context, understanding and anticipating the robot intentions ease the completion of a joint-task. Whereas previous work has sought to explicitly optimize the legibility of behavior, we

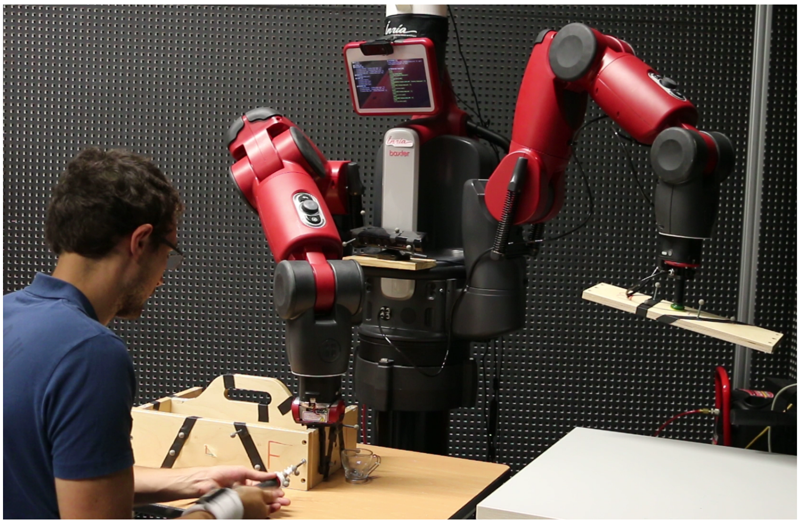

Figure 15. Interactive cooperative task learning.

investigate legibility as a property that arises automatically from general requirements on the efficiency and robustness of joint human-robot task completion.

Following our previous work on legibility of robot motions [56], we have conducted several user experiments to analyze the effects of the policy representation on the universality of the legibility.

This work lead to a submission of a journal article to the International Journal of Social Robotics (IJSR) under the special issue: Towards a Framework for Joint Action. The article has been accepted with minor revisions and is currently in the final stage of the review process.

7.2.2.4. Postural optimization for a safe and comfortable human-robot interaction

When we, humans, accomplish a task our body posture is (partially) constrained. For example, acting on an object constrains the pose of the hand relatively to the object, and the head faces the object we are acting upon. But due to the large number of degrees of freedom (DOF) of the human body, other body parts are unconstrained and several body postures are viable with respect to the task. However, not all of them are viable in terms of ergonomics. Using a personalized human model, observational postural assessment techniques can be automatized. Optimizing the model body posture is then the logical next step to find an ergonomically correct posture for the worker to accomplish a specific task.

To optimize the subject's model to achieve a specific task, we define an objective function that minimizes the efforts of the whole body posture, based on the Rapid Entire Body Assessment (REBA) technique [135]. The objective function also account for visibility of the target object and worker's laterality. We have also implemented an automatic assessment of the worker's body posture based on the REBA method.

Using a spherical object, carried by a Baxter humanoid robot as illustrated in Fig. 16, we mimic an industrial scenario where the robot helps the worker by positioning and orienting an object in which the worker has to insert specific shapes. In a user-study with forty participants, we compare three different robot's behaviors, one of them being the result of the postural optimization of the subject's personalized model. By the mean of a survey session, and the online assessment of the subject's posture during the interaction, we prove that our method leads to a safer posture, and is perceived as more comfortable.

This work has been submitted to the IEEE Robotics and Automation Letters (RA-L) with the ICRA conference option and is currently under review.

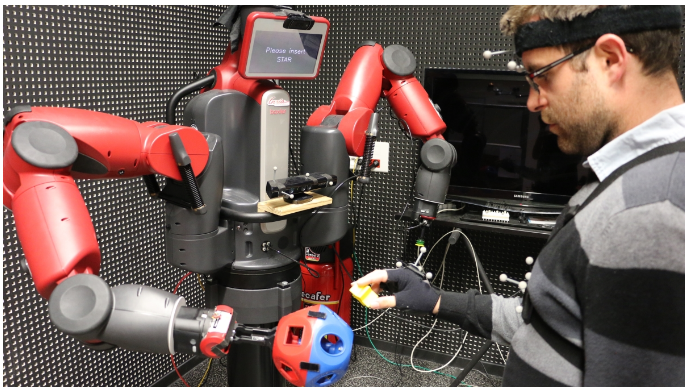

Figure 16. Representation of the setup considered in the user study. The robot presents to the user a spherical ball in which multiple shapes can be inserted. Final pose of the object is calculated from the user posture at his current location. Body motions during the insertion are recorded using a suit made from OptiTrack markers.

7.3. Representation Learning

Participants: David Filliat [correspondant], Celine Craye, Yuxin Chen, Clement Masson, Adrien Matricon, Freek Stulp.

7.3.1. Incremental Learning of Object-Based Visual Saliency

Searching for objects in an indoor environment can be drastically improved if a task-specific visual saliency is available. We describe a method to learn such an object-based visual saliency in an intrinsically motivated way using an environment exploration mechanism. We first define saliency in a geometrical manner and use this definition to discover salient elements given an attentive but costly observation of the environment. These elements are used to train a fast classifier that predicts salient objects given large-scale visual features. In order to get a better and faster learning, we use intrinsic motivation to drive our observation selection, based on uncertainty and novelty detection. Our approach has been tested on RGB-D images, is real-time, and outperforms several state-of-the-art methods in the case of indoor object detection. We published these results in two conferences [78],[77].

7.3.2. Cross-situational noun and adjective learning in an interactive scenario

Learning word meanings during natural interaction with a human faces noise and ambiguity that can be solved by analysing regularities across different situations. We propose a model of this cross-situational learning capacity and apply it to learning nouns and adjectives from noisy and ambiguous speeches and continuous visual input. We compared two different topic models for this task: Non Negative Matrix Factorization and Latent Dirichlet Association. We present experiments on learning object names and color names showing the performance of these model on realistic data and show how active learning can be used to speed-up learning by letting the learner choose the objects to be described. We published these results in a conference paper [75]

7.3.3. Learning representation with gated auto-encoders

We investigated algorithms that would be able to learn relevant visual or multi-modal features from data recorded while the robot performed some task. Representation learning is a currently very active research field, mainly focusing on deep-learning, which investigates how to compute more meaningful features from the raw high dimensional input data, providing a more abstract representation from which it should be easier to make decision or deduction (e.g classification, prediction, control, reinforcement learning). In the context of robotics, it is notably interesting to apply representation learning in a temporal and multi-modal approach exploiting vision and proprioception so as to be able to find feature that are relevant for building models of the robot itself and of its actions and their effect on the environment. Among the many existing approaches, we decided to explore the use of gated auto-encoders [104], a particular kind of neural networks including multiplicative connections, as they seem well adapted to this problem. Preliminary experimentations have been carried out with gated auto-encoders to learn transformations between two images. We observed that Gated Auto-Encoders (GAE) can successfully find compact representations of simple transformations such as translations, rotation or scaling between two small images. This is however not directly scalable to realistic images such as ones acquired by a robot's camera because of the number of parameters, memory size and compational power it would require (unless drastically downsampling the image which induces sensible loss of information). In addition, the transformation taking an image to the next one can be the combination of transformations due to the movement of several object in the field of view, composed with the global movement of the camera. This induces the existence of an exponential number of possible transformations to model, for which the basic GAE architecture is not suited.

7.3.4. Incremental Learning in high dimensions

Participants: Alexander Gepperth [correspondant], Cem Karaoguz.

7.3.4.1. Incremental learning in data spaces of high dimensionality

Currently existing incremental learning algorithms in robotics have achieved a relatively high degree of usability due to the reduction of free model parameters in such approaches LWPR. Indeed, such algorithms are usually applied to low-dimensional tasks such as graspin with very good success, as the incremental learning paradigm is very appropriate to the robotics domain in general, especially in interactive scenarios. On the other hand, the partitioning of input space that is performed by LWPR and related approaches fails to be applicable if data dimension exceeds 50 elements since the used covariance matrices grow quadratically in size w.r.t. data dimensionality. Therefore, especially the incremental treatment of visual information is difficult, particularly for recognition and classification of objects or obstacles in general. To remedy this, we developed the incremental learning algorithm PROPRE [130] of fixed model complexity that can easily deal with data dimensionalities of 10.000 and beyond, where the only assumption is the same that is explicitly made for LWPR: that the data has structure, i.e., lies on a low-dimensional sub-manifold. We demonstrated the feasibility of the algorithm on several realistic datasets, on the one hand MNIST and on the other hand a much more challenging visual pedestrian pose recognition task from the intelligent vehicle domain[65].

7.3.4.2. Incremental learning with two memory systems

In order to increase PROPRE's ability to react quickly to changes in data statistics (e.g., a newly added visual class) while at the same time avoiding fast forgetting, a second, short-term memory system was proposed for PROPRE in [65]. This short-term memory is filled when task failures occur and is used to re-train the incremental long-term memory at a later time and on a slower time scale. In this way, abrupt changes in data statistics maybe immediately reacted upon, whereas the long-term memory can retain its stability that ensures that any forgetting happens gradually, on a determined time scale.

7.3.4.3. Steps towards incremental deep learnig

Since PROPRE is a neural architecture with just one hidden layer, its capacity is limited. This is why steps were taken to create deeper hierarchies with PROPRE in afashion totally analogous to current deep learning approaches. First of all, it was shown that a deep PROPRE architecture can achieve the same classification accuracy on MNIST as a shallow one but at a significantly lower computational cost [86]. Furthermore, it was shown that a deep PROPRE architecture is capable of change detection at multiple levels, a prerequisite for incremental learning [87]. Next steps will consist of creating regular deep PROPRE architectures and testing them on curently accepted machine learning benchmark tasks.

7.3.4.4. Real-world application of incremental learning

In [88], the incremental PROPRE algorithm was applied to object recognition and detection problems in the domain of intelligent vehicles. I was shown that, by re-casting pedestrian detection as an incremental learning problem where the background class is added only after learnig the pedestrian class, the number of required model resources for representing the background is reduced, and better accuracy can be obtained.

7.3.5. *Measuring Uncertainty in Deep Learning Networks*

Participants: Florian Golemo [correspondant], Manuel Lopes.

As precursor to the main objective of the IGLU project, we investigated methods that would enable deep neural networks to judge their knowledge about a domain.

Neural networks, especially deep ones, have been shown to be able to model arbitrarily complex problems, and thus offer powerful tools for machine learning. Yet they come with a significant flaw of not being inherently able to represent certainty of their predictions. By adding a measure of uncertainty to neural networks, this technology could be applied to autonomous exploration and open-ended learning tasks.

Thus the goal of this project was to find a method to measure how much knowledge a neural network has about about an unlabeled data item (measure of uncertainty), and to apply this new measure in an active learning context. The objective of the latter was to demonstrate the efficiency in handpicking interesting data, to optimally extend the system's own capabilities.
We were successful in finding a measure of uncertainty that would reliably distinguish data that the network has seen before, from data that was generally unfamiliar to the network. This measure was created by measuring the entropy of the network's last layer across a batch of stochastic samples generated by adding Poisson noise to the inputs.
The measure failed however to outperform random sampling in several active learning scenarios. Yarin Gal published related work as part of his dissertation [129] after this project was concluded. He elaborated that deep neural networks are very effective in canceling out input noise. The author suggested to use existing "Dropout" layers instead for stochastic sampling, but he reaches the same conclusion of using the last layer entropy as measure of uncertainty.

7.3.6. *Learning models by minimizing complexity*

We introduce COCOTTE (COnstrained Complexity Optimization Through iTerative merging of Experts), an iterative algorithm for discovering discrete, meaningful parameterized skills and learning explicit models of them from a set of behaviour examples. We show that forward-parameterized skills can be seen as smooth components of a locally smooth function and, framing the problem as the constrained minimization of a complexity measure, we propose an iterative algorithm to discover them. This algorithm fits well in the developmental robotics framework, as it does not require any external definition of a parameterized task, but discovers skills parameterized by the action from data. An application of our method to a simulated setup featuring a robotic arm interacting with an object is shown. This work was published in a conference paper [83]

7.4. Applications for Robotic myoelectric prostheses: co-adaptation algorithms and design of a 3D printed robotic arm prosthesis

Participants: Pierre-Yves Oudeyer [correspondant], Manuel Lopes, Mathilde Couraud, Sebastien Mick, Aymar de Rugy, Daniel Cattaert, Florent Paclet.

Together with the Hybrid team at INCIA, CNRS, the Flowers team continued to work on establishing the foundations of a long-term project related to the design and study of myoelectric robotic prosthesis. The ultimate goal of this project is to enable an amputee to produce natural movements with a robotic prosthetic arm (open-source, cheap, easily reconfigurable, and that can learn the particularities/preferences of each user). This will be achieved by 1) using the natural mapping between neural (muscle) activity and limb movements in healthy users, 2) developing a low-cost, modular robotic prosthetic arm and 3) enabling the user and the prosthesis to co-adapt to each other, using machine learning and error signals from the brain, with incremental learning algorithms inspired from the field of developmental and human-robot interaction. In particular, in 2016 two lines of work were achieved, concerning two important scientific challenges, and in the context of one PEPS CNRS projects:

First, a new version of the experimental setup was designed to allow fast prototyping of 3D printed robotic prostheses. This work was based on the use of the Poppy open-source modular platform, and resulted in a functional prototype. A video demonstrations is available at: https://github.com/s-mick

Second, we have designed various control models allowing to transform signals coming from the human arm (either measured through EMGs or direct force sensors) and we have studied the influence of control modes on usability in the operation of a robotic arm prosthesis. In this context, we designed an experimental framework centered on a target-reaching task, and carried out tests with healthy subjects. The usability assessment relies on performance metrics on one hand, and a post-experiment questionnaire on another hand, in order to explore the multiple dimensions of the system's usability rather than focus only on measurements evaluating skills and performances. The code associated to this experimental setup is open-source and available at https://github.com/s-mick.

7.5. Applications for Educational Technologies

7.5.1. Multi-Armed Bandits for Adaptive Personalization in Intelligent Tutoring Systems

Participants: Manuel Lopes [correspondant], Pierre-Yves Oudeyer, Didier Roy, Alexandra Delmas, Benjamin Clement.

7.5.1.1. The Kidlearn project

Kidlearn is a research project studying how machine learning can be applied to intelligent tutoring systems. It aims at developing methodologies and software which adaptively personalize sequences of learning activities to the particularities of each individual student. Our systems aim at proposing to the student the right activity at the right time, maximizing concurrently his learning progress and its motivation. In addition to contributing to the efficiency of learning and motivation, the approach is also made to reduce the time needed to design ITS systems.

We present an approach to Intelligent Tutoring Systems which adaptively personalizes sequences of learning activities to maximize skills acquired by students, taking into account the limited time and motivational resources. At a given point in time, the system proposes to the students the activity which makes them progress faster. We introduce two algorithms that rely on the empirical estimation of the learning progress, **RiARiT** that uses information about the difficulty of each exercise and **ZPDES** that uses much less knowledge about the problem.

The system is based on the combination of three approaches. First, it leverages recent models of intrinsically motivated learning by transposing them to active teaching, relying on empirical estimation of learning progress provided by specific activities to particular students. Second, it uses state-of-the-art Multi-Arm Bandit (MAB) techniques to efficiently manage the exploration/exploitation challenge of this optimization process. Third, it leverages expert knowledge to constrain and bootstrap initial exploration of the MAB, while requiring only coarse guidance information of the expert and allowing the system to deal with didactic gaps in its knowledge. The system is evaluated in a scenario where 7-8 year old schoolchildren learn how to decompose numbers while manipulating money. Systematic experiments are presented with simulated students, followed by results of a user study across a population of 400 school children. [14]

7.5.1.2. A Comparison of Automatic Teaching Strategies for Heterogeneous Student Populations

Online planning of good teaching sequences has the potential to provide a truly personalized teaching experience with a huge impact on the motivation and learning of students. In this work we compare two main approaches to achieve such a goal, POMDPs that can find an optimal long-term path, and Multi-armed bandits that optimize policies locally and greedily but that are computationally more efficient while requiring a simpler learner model. Even with the availability of data from several tutoring systems, it is never possible to have a highly accurate student model or one that is tuned for each particular student. We study what is the impact of the quality of the student model on the final results obtained with the two algorithms. Our hypothesis is that the higher flexibility of multi-armed bandits in terms of the complexity and precision of the student model will compensate for the lack of longer term planning featured in POMDPs. We present several simulated results showing the limits and robustness of each approach and a comparison of heterogeneous populations of students.

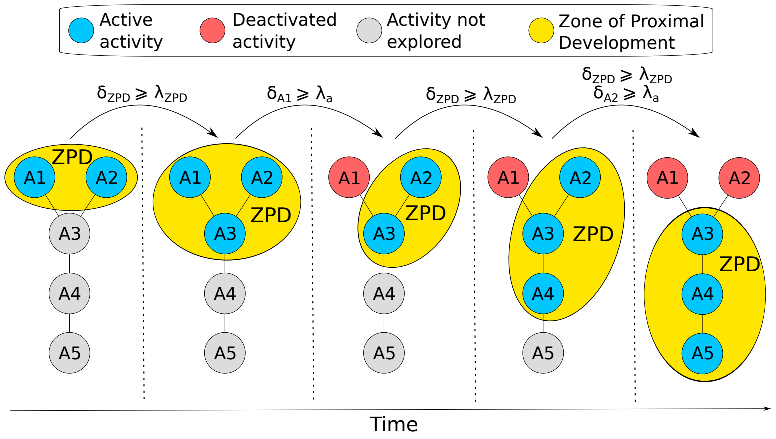

Figure 17. ZPDES exploration of an activity graph, with δ_{ZDP} the success rate over all active activities, λ_{ZPD} the threshold to expand the ZPD, δ_{Ax} the success rate for the activity Ax, and λ_a the threshold to reach to deactivate an activity.

This work has been publish and presented at Educational Data Mining 2016 conference in Raleigh, USA [76].

Github link of the experiments paper code : https://github.com/flowersteam/kidlearn/tree/edm2016

7.5.1.3. The KidBreath project

To create learning contents linked to asthma to personalize it like mathematics activities in Kidlearn project [14] we used recommandation criterias in Therapeutic Education Program for asthma kids made by Health High Autority. Following an approach of participatory design [114], contents were validated by medical experts like health educators, pulmonoligists and pediatrics. Then, we conducted a workshop with forty kids aged 8 in order to iterate over the application interfaces and evaluate enjoy about it with observations. Finally, we realized a focus group with 5 asthma kids to validate the global comprehension of a part of the content. It revealed that children wanted more contents about the crisis treatment and how the asthma works in the human system (verbatims).

In a preliminary study, we experimented two conditions in 20 control children (with 3 asthma kids), one giving the possibility of choosing activities like the child wants, and one no giving this choice (activities displayed in random). No significative difference between the two groups, but results showed KidBreath was easy to use with scores > 75 using System Usability Scale [115]. Based on Cordova and Lepper works to evalueate motivation and knowledge with similar system and population [121], children had their disease knowledge increased with just one week use and were motivated using it. Finally, asthma kids showed they were more engaged than healthy kids and used KidBreath more seriously (stayed in breaks). These results was presented in the 5th edition of Serious Games in Medicine Conference in Nice.

We presented Thesis project in some events this year, with one publication surbmitted and validated:

- 2nd Meeting for Aquitaine and Euskadi companies in Biology and Health Between, February 11th 2016 in San sebastian (poster),
- Hackathon of innovation in pulmonary diseases, Respirhacktion, September 16th to 18th 2016 in Paris (project development in hackathon),
- 5th Conference in Health Ergonomics and Patient Safety, October 5th to 7th 2016 (poster) [102],
- Learning Lab day, November 16th in Inria Paris (oral presentation of project),
- 5th edition of Serious Games in Medicine Conference, December 2nd to 3rd 2016 in Nice Sofia-Antipolis University (oral presentation).

7.5.2. Poppy Education: Designing and Evaluating Educational Robotics Kits

Participants: Pierre-Yves Oudeyer [correspondant], Didier Roy, Théo Segonds, Stéphanie Noirpoudre, Marie Demangeat, Thibault Desprez, Matthieu Lapeyre, Pierre Rouanet, Nicolas Rabault.

The Poppy Education project aims to create, evaluate and disseminate all-inclusive pedagogical kits, open-source and low cost, for teaching computer science and robotics.

It is designed to help young people to take ownership with concepts and technologies of the digital world, and provide the tools they need to allow them to become actors of this world, with a considerable socio-economic potential. It is carried out in collaboration with teachers and several official french structures (French National Education, High schools, engineer schools, ...). For secondary education and higher education, scientific literacy centers, Fablabs.

Poppy Education is based on the robotic platform poppy (open-source platform for the creation, use and sharing of interactive 3D printed robots), including:

- Poppy Humanoid, a robust and complete robotics platform designed for genuine experiments in the real world and can be adapted to specific user needs.
- Poppy Torso, a variant of Poppy Humanoid that can be easily installed on any flat support.
- Ergo Jr, a robotic arm. Durable and inexpensive, it is perfect to be used in class. Python. Directly from a web browser, using Ipython notebooks (an interactive terminal, in a web interface for the Python Programming Language).
- Snap. The visual programming system Snap, which is a variant of Scratch. Its features allow a thorough introduction of information technology.
- C++, Java, Matlab, Ruby, Javascript, etc. thanks to a REST API that allows you to send commands and receive information from the robot with simple HTTP requests.
- Virtual robots (Poppy Humanoid, Torso and Ergo) can be simulated with the free simulator V-REP. It is possible in the classroom to work on the simulated model and then allow students to run their program on the physical robot.

7.5.2.1. Pedagogical experimentations : Design and experiment robots and the pedagogical activities in classroom

This project is user centred design. The pedagogical tools of the project (real and virtual robots, pedagogical activities, etc.) are being created directly with the users and evaluated in real life by experiments. For our experimentations in the classroom we are mainly using the robot Poppy Ergo Jr (real and virutal) and Snap! Our purpose is to improve this pedagogical tools and to create pedagogical activities and resources for teachers.

- A pedagogical working group:

  At the beginning of the project, we established a pedagogical working group of 12 volunteers, teachers from different level (mainly high school teachers of the Aquitaine region) to help to design educational activities in line with the needs of the school curriculum and to test them in the classroom.

  At the beginning of the second year of the project we added 7 other teachers from different background (middle-school and high school teachers) into the group to add more diversity.

  We organised some training to help them to discover and learn how to use the robotics platform, then we met monthly to exchange about the project and to get some feedbacks from them.

  You can see the videos of pedagogical robotics activities here:
  https://www.youtube.com/playlist?list=PLdX8RO6QsgB7hM_7SQNLvyp2QjDAkkzLn

- Experiment and Evaluate the pedagogical kits:

  Some engineer of the Poppy Education team went to visit the teachers in their school to see and to evaluate the pedagogical tools (robot and activities) in real contexts of use.

Figure 18. Experiment robots and pedagogical activities in classroom

In addition to the observations in classroom, two trainee students of Master 2 in cognitive sciences (M. Demangeat, D. Thibaut) have established an experimental protocol to evaluate the utility and the integration of the pedagogical kits in class. They created and filled out questionnaires by teachers and students. The analyzes of the results are presented in their paper thesis.

This experimentations are helping us to understand the educational needs, to create and improve the pedagogical tools.

7.5.2.2. Partnership on education projects

- Ensam

  The Arts and Métiers campus at Bordeaux-Talence in partnership with Inria wishes to contribute to its educational and scientific expertise to the development of new teaching methods and tools. The objective is to develop teaching sequences based on a project approach, relying on an attractive multidisciplinary technological system: the humanoid Inria Poppy robot.

  The humanoid Inria Poppy robot offers an open platform capable of providing an unifying thread for the different subjects covered during the 3-years of the Bachelor training: mechanics, manufacturing (3D printing), electrical, mecha-tronics, computer sciences, design.

  Last year student of "bachelor degree" (ENSAM-Talence) have designed, manufactured, assembled and programmed 4 different solutions to replace the fixed hand of Poppy by a gripper device: https://www.youtube.com/watch?v=DZjGaJk2fQk

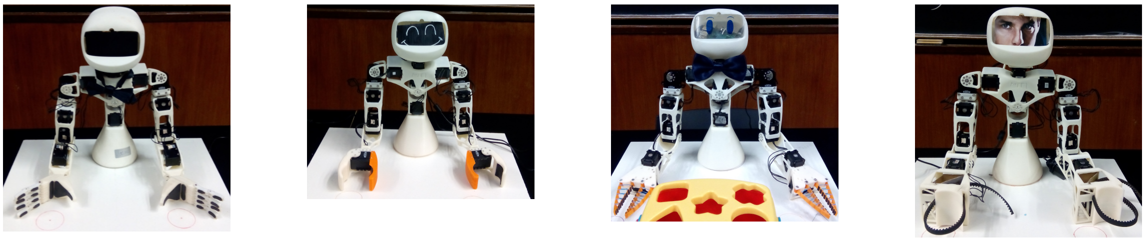

Figure 19. 4 grippers hands designed by students

- Audiovisual Students project

  Students from the BTS audiovisual of Saint-Genes La Salle have created a complete video report on the Poppy project to highlight the use in education and art:
  https://www.youtube.com/watch?v=NMwwH7AWO2Q

- Poppy entre dans la danse (Poppy enters the dance)

  The project "Poppy enters the dance" (Canope 33) uses the humanoid robot Poppy, able to move and experience the dance. The purpose of this project is to allow children to understand the interactions between science and choreography, to play with the random and programmable, to experience movement in dialogue with the machine. At the beginning of the project they attended two days of training on the humanoid robot (Inria - Poppy Education). During the project, they met the choreographer Eric Minh Cuong Castaing and the engineer Segonds Theo (Inria - Poppy Education).

  You can see an overview of the project with kindergarten students :
  https://www.youtube.com/watch?v=XB9IXwcfJo0

7.5.2.3. Created pedagogical documents and resources

- Rebuilt the documentation of Poppy-project

  It was necessary for us to have an accessible and clear documentation to help teachers to use and create projects with the robots in the classroom so we rebuilt the existing documentation of the robotics platform Poppy. We added and improve the contents and we used the platform gitbook :
  https://docs.poppy-project.org/en/

- Pedagogical booklet

  The pedagogical booklet [96] brings together all the pedagogical activities and project testing in the classroom. It provides guided activities, small challenges and projects to become familiar with the Poppy Ergo Jr robot and the Programming language Snap!
  https://drive.google.com/file/d/0B2jV8VX-lQHwTUxXZjF3OGxHVGM/view

Apprendre à programmer Poppy Ergo Jr en Snap!

Ce livret propose des activités et des petits défis à réaliser pour se familiariser avec le robot Poppy Ergo Jr et le langage de programmation Snap!.

for Education poppy

N'hésitez pas à nous rejoindre sur notre forum (forum.poppy-project.org, catégorie Education) pour partager vos productions et poser toutes les questions que vous souhaitez !

Partie 2 : *Programmer par démonstration*

Le robot Poppy Ergo Jr est capable de mesurer en temps réel la position de ses moteurs. Ainsi lorsqu'on les fait bouger manuellement, il peut **enregistrer les mouvements effectués pour les reproduire ulterieurement.**

19

Partie 5 : *Si... alors... !*

Un branchement conditionnel de type Si... Alors... permet de faire exécuter des instructions selon si une condition donnée est vraie ou non.

37

Figure 20. Pedagogical booklet: learn to program the robot Poppy Ergo Jr in Snap!

The pedagogical activities are also available on the Poppy project forum where everyone is invited to comment and create new ones:
https://forum.poppy-project.org/t/liste-dactivites-pedagogiques-avec-les-robots-poppy/2305

- Guide on the pedagogical use of the kit Poppy Ergo Jr in classroom

  We wrote an article [95] to explain how to use the Robot Ergo Jr in a classroom. It includes a summary of the characteristics of the robots, activities example and give all the necessary resources: https://pixees.fr/dans-la-famille-poppy-je-voudrais-le-robot-ergo-jr
- Demonstration guide to introduce the project

  This document is for people who already have a little experience with the Poppy Ergo Jr robot and snap! and wishing to present the project (i.e: to a colleague/acquaintance, on a exhibition stand, during a conference).

  The purpose of this document is to provide the necessary elements to enable the Poppy Education project to be presented through the use of Poppy Ergo Jr. robot. The key points of the Poppy Education project and the features of Poppy Ergo Jr kit are presented as well as examples of demonstrations of educational activities (videos and snap! projects) and educational projects (videos). An example of structuring a demo is provided at the end of the document.
  https://forum.poppy-project.org/t/guide-de-demo-du-kit-pedagogique-poppy-ergo-jr-version-beta/2698
- Model of pedagogical activities sheet

  We designed a model of pedagogical activity sheet. It helps us to get back the various activities and allows to have a homogeneous presentation. It is simpler to share and get back the creations of each.
  https://forum.poppy-project.org/t/modele-de-fiche-pedagogique-telechargeable-pour-les-activites-robotiques/2706

7.5.2.4. Scientific mediation

To promote educational uses of the platform, we participated in events (conference, seminar etc.).

We participated as well at some workshops to introduce students to robotics and programming.

7.5.2.5. Symposium robotics

We organized a symposium robotics (http://dm1r.fr/colloque-robotique-education/) that present research results and feedback on the use of Poppy and Thymio robots in education (other robots have been discussed, such as BeeBot and Metabot), from kindergarten to higher education, The Centers for Scientific and Technical Culture.

It was a 2 day event : 200 participants, 40 speakers (conferences and workshops).

Poppy Education team and the working group teachers helped with the organisation of the event and during the event (talk and workshops).

All conference videos are available on the web :
https://www.youtube.com/watch?v=prFmC-BpdY8&index=1&list=PL9T8000j7sJBC_H3L_hS-i4Ltlh1Fz2FY

7.5.3. IniRobot: Educational Robotics in Primary Schools

Participants: Didier Roy [correspondant], Pierre-Yves Oudeyer.

IniRobot (a project done in collaboration with EPFL/Mobsya) aims to create, evaluate and disseminate a pedagogical kit which uses Thymio robot, open-source and low cost, for teaching computer science and robotics.

IniRobot Project consists to produce and diffuse a pedagogical kit for teachers and animators, to help to train them directly or by the way of external structures. The aim of the kit is to initiate children to computer science and robotics. The kit provides a micro-world for learning, and takes an enquiry-based educational approach, where kids are led to construct their understanding through practicing an active investigation methodology within teams. It is based on the use of the Thymio II robotic platform. More details about this projects were published in RIE 2015 [50] , which presents the detailed pedagogical objectives and a first measure of results showing that children acquired several robotics-related concepts. See also http://www.inirobot.fr.

Deployment: After 24 months of activity, IniRobot is used by about 1400 adults and 16 000 children in 54 cities of France. Example of action in university: MEEF teacher training for the hope of Aquitaine. Example of action in school: training of all Gironde Pedagogical ICT Advisors, covering nearly 1000 schools. Example of action in the extracurricular time: training 82 facilitators TAP cities of Talence, Pessac, Lille, ..., CDC Gates of inter-seas. Example of national action: Training of the digital mediators of the 8 Inria centers.

7.5.3.1. Partnership

The project is carried out in main collaboration with the LSRO Laboratory from EPFL (Lausanne) and others collaborations with French National Education/Rectorat d'Aquitaine, with Canopé Educational Network, with ESPE (teacher's school) Aquitaine, ESPE Martinique, ESPE Poitiers, National Directorate of Digital Education

7.5.3.2. Created pedagogical documents and resources

- IniRobot pedagogical kit [94]: This pedagogical booklet provides activities scenarized as missions to do. A second pedagogical booklet has been also created by three pedagogical advisers for primary school, with pedagogical instructions and aims, under ou supervision. http://tice33.ac-bordeaux.fr/Ecolien/ASTEP/tabid/5953/language/fr-FR/Default.aspx A new pedagogical kit is in progress, Inirobot Scratch, which will propose activities with Scratch and Snap! and Thymio robot.
- Inirobot website and forum http://www.inirobot.fr With this website, teachers, animators and general public can download documents, exchange about their use of inirobot' kit.
- Publication about Inirobot and Poppy Education A poster and talk were produced in Didapro-Didastic 6 Conference in Namur (Belgium) on 2016 January. [99]

7.5.3.3. Scientific mediation

Inirobot is very popular and often presented in events (conferences, workshops, ...) by us and by others.

7.5.3.4. Symposium robotics

With Poppy Education, Inirobot is a main line in our colloquium "Robotics and Education" (http://dm1r.fr/colloque-robotique-education/)

8. Bilateral Contracts and Grants with Industry

8.1. Bilateral Contracts with Industry

8.1.1. Autonomous Driving Commuter Car

Participants: David Filliat [correspondant], Emmanuel Battesti.

We further developed a planning algorithm for a autonomous electric car for Renault SAS in the continuation of the previous PAMU project. We improved our planning algorithm in order to go toward navigation on open roads, in particular with the ability to reach higher speed than previously possible, deal with more road intersection case, and with multiple lane roads (overtake, insertion...).

8.2. Bilateral Grants with Industry

8.2.1. Curiosity and visual attention

Participants: David Filliat [correspondant], Celine Craye.

Financing of the CIFRE PhD grant of Celine Craye by Thales S.A. with the goal of developing a mechanism of visual attention guiding the exploration of a robot.

8.2.1.1. Adaptive device for disease awareness and treatment adherence of asthma in children

Participants: Manuel Lopes [correspondant], Alexandra Delmas, Pierre-Yves Oudeyer.

Financing of the CIFRE PhD grant of Alexandra Delmas by Itwell with the goal of developing a tool for self-learning for patients to improve their compliance to treatment.

9. Partnerships and Cooperations

9.1. Regional Initiatives

9.1.1. Poppy Education

Poppy Education

Program: Feder - Région Aquitaine

Duration: January 2014 - December 2017

Coordinator: PY Oudeyer, Inria Flowers

Partners: Inria Flowers

Funding: 1 million euros (co-funded by Feder/EU Commission, Region Aquitaine and Inria)

Poppy Education aims to create, evaluate and disseminate pedagogical kits “turnkey solutions” complete, open-source and low cost, for teaching computer science and robotics. It is designed to help young people to take ownership with concepts and technologies of the digital world, and provide the tools they need to allow them to become actors of this world, with a considerable socio-economic potential. It is carried out in collaboration with teachers and several official french structures (French National Education/Rectorat, Highschools, engineering schools, ...). It targets secondary education and higher education, scientific literacy centers, Fablabs.

Poppy robotic platform used in the project is free hardware and software, printed in 3D, and is intended primarily for:

- learning of computer science and robotics,
- introduction to digital manufacturing (3D printing ...)
- initiation to the integration of IT in physical objects in humanoid robotics, mechatronics.
- artistic activities.

Educational sectors covered by the project are mainly: Enseignement d’exploration ICN en seconde, enseignement ISN en terminale S et bientôt en 1ère , filière STI2D, MPS seconde. Web: http://www.poppy-project.org/education .

9.1.2. ENSAM

The orientation of a (high school) student, choosing a career, is often based on an imagined representation of a discipline, sector of activity or training. Moreover, higher education is sometimes for a college student or a student a self centered universe, with inaccessible teaching methodologies and level of competence.

The Arts and Métiers campus at Bordeaux-Talence in partnership with Inria contributes with its educational and scientific expertise to the development of new teaching methods and tools. The objective is to develop teaching sequences based on a project approach relying on an attractive multidisciplinary technological system: the humanoid Inria Poppy robot. These teaching sequences will be built and tailored to different levels of training, from high schools to Engineer schools.

The new formation "Bachelor of Technology", started in September 2014 at Ensam Bordeaux, is resolutely turned towards a project based pedagogy, outlining concepts from concrete situations. The humanoid Inria Poppy robot offers an open platform capable of providing an unifying thread for the different subjects covered during the 3-years of the Bachelor formation: mechanics, manufacturing (3D printing), electrical, mechatronics, computer sciences, design…

For the 1st and 2nd year of the ENSAM Engineer cursus, the Poppy robot is now used to support the teaching and to conduct further investigation.

9.1.3. KidLearn and Region Aquitaine

A Conseil Régional d'Aquitaine Project (KidLearn, 2015-) began, coordinated by Manuel Lopes entitled KidLearn. Will fund 50% of a 3 years PhD student.

We propose here a research project that aims at elaborating algorithms and software systems to help humans learn efficiently, at school, at home or at work, by adapting and personalizing sequences of learning activities to the particularities of each individual student. This project leverages recent innovative algorithmic models of human learning (curiosity in particular, developed as a result of ERC European project of the Flowers team), and combines it with state-of-the-art optimization algorithms and an original integration with existing expert knowledge (human teachers). Given a knowledge domain and a set of possible learning activities, it will be able to propose the right activity at the right time to maximize learning progress. It can be applied to many learning situations and potential users: children learning basic knowledge in schools and with the support of their teachers, older kids using educational software at home, of adults needing to acquire new skills through professional training ("formation professionnelle"). Because it combines innovations in computational sciences (machine learning and optimization) with theories of human cognition (theories of human learning and of education), this project is also implementing a strong cross-fertilization between technology and human sciences (SHS).

9.1.4. Comacina Capsule Creative Art/Science project and Idex/Univ. Bordeaux

The artist community is a rich source of inspiration and can provide new perspectives to scientific and technological questions. This complementarity is a great opportunity that we want to enforce in the Poppy project by making the robot accessible to non-robotic-expert users. The Comacina project, in collaboration with the Flowers team and supported by funding from Idex/Univ. Bordeaux, explored the role of movements and light in expressing emotions. This project was implemented through several residencies during the year, and several performances at various cultural places in Aquitaine, including at Pole Evasion in Ambares-et-Lagrave. a report is available at https://flowers.inria.fr/RencontreAutourDuGeste.pdf . It benefitted from funding from the Art/Science Idex call for project.

9.2. National Initiatives

PY Oudeyer and M Lopes collaborated with Aymar de Rugy, Daniel Cattaert and Florent Paclet (INCIA, CNRS/Univ. Bordeaux) about the design of myoelectric robotic prostheses based on the Poppy platform, and on the design of algorithms for co-adaptation learning between the human user and the prosthesis. This was funded by a PEPS CNRS grant.

D. Roy is the Inria leader of project "Ecole du code" http://www.ecoleducode.net/ which provides teachers and animators formations and learning games to initiate young people to computer science and robotics.

D. Roy is member of the Class'code team (Inria is member of the consortium of this project) https://pixees.fr/classcode/accueil/. Class'code is a blended formation for teachers and animators who aim to initate young people to computer science and robotics. D. Roy has in charge the robotics module of the project.

D. Roy is member of the organization of computer science exhibition in "Palais de la découverte" which will begin on 2017 September for three years. He participates for robotics part.

D. Roy is member of the Scratch Conference (Bordeaux, 2017 July) organization team.

D. Roy is member of the team "Education en Scène" which organize educational activities with robotics in Bordeaux Digital City (2017 July).

D. Roy is member of "CRIC" Project, about Robotics in Vocational Schools, with Canope Ile de France, Lutin Userlab (Cité des SCiences), CNAM.

D. Roy is project leader of Thymio Simulator for Classcode project. Specifications and coordination of work.

D. Roy is project leader of Thymio Scratch and Thymio Snap! development, with D. Sherman. Inria, EPFL and Mobsya collaboration.

Around Robotics for education, many collaborations were put in place. With the LSRO Laboratory from EPFL (Lausanne) and others collaborations with French National Education/Rectorat d'Aquitaine, with Canopé Educational Network, with ESPE (teacher's school) Aquitaine, ESPE Martinique, ESPE Poitiers, National Directorate of Digital Education, Fondation "La Main à la Pâte", Maison for Science in Bordeaux University, Orange Fondation.

9.3. European Initiatives

9.3.1. FP7 & H2020 Projects

9.3.1.1. 3rd HAND

Title: Semi-Autonomous 3rd Hand

Programm: FP7

Duration: October 2013 - September 2017

Coordinator: Inria

Partners:

- Technische Universität Darmstadt (Germany)
- Universität Innsbruck (Austria)
- Universität Stuttgart (Germany)

Inria contact: Manuel Lopes

Robots have been essential for keeping industrial manufacturing in Europe. Most factories have large numbers of robots in a fixed setup and few programs that produce the exact same product hundreds of thousands times. The only common interaction between the robot and the human worker has become the so-called 'emergency stop button'. As a result, re-programming robots for new or personalized products has become a key bottleneck for keeping manufacturing jobs in Europe. The core requirement to date has been the production in large numbers or at a high price.Robot-based small series production requires a major breakthrough in robotics: the development of a new class of semi-autonomous robots that can decrease this cost substantially. Such robots need to be aware of the human worker, alleviating him from the monotonous repetitive tasks while keeping him in the loop where his intelligence makes a substantial difference.In this project, we pursue this breakthrough by developing a semi-autonomous robot assistant that acts as a third hand of a human worker. It will be straightforward to instruct even by an untrained layman worker, allow for efficient knowledge transfer between tasks and enable a effective collaboration between a human worker with a robot third hand. The main contributions of this project will be the scientific principles of semi-autonomous human-robot collaboration, a new semi-autonomous robotic system that is able to: i) learn cooperative tasks from demonstration; ii) learn from instruction; and iii) transfer knowledge between tasks and environments. We will demonstrate its efficiency in the collaborative assembly of an IKEA-like shelf where the robot acts as a semiautonomous 3rd-Hand .

9.3.1.2. DREAM

Title: Deferred Restructuring of Experience in Autonomous Machines

Programm: H2020

Duration: January 2015 - December 2018

Coordinator: UPMC

Partners:

- Armines (ENSTA ParisTech)
- Queen Mary University London (England)

University of A Coruna (Spain)

Vrije University Amsterdam (Holland)

Contact: David Filliat

Abstract: A holy grail in robotics and artificial intelligence is to design a machine that can accumulate adaptations on developmental time scales of months and years. From infancy through adult- hood, such a system must continually consolidate and bootstrap its knowledge, to ensure that the learned knowledge and skills are compositional, and organized into meaningful hierarchies. Consolidation of previous experience and knowledge appears to be one of the main purposes of sleep and dreams for humans, that serve to tidy the brain by removing excess information, to recombine concepts to improve information processing, and to consolidate memory. Our approach – Deferred Restructuring of Experience in Autonomous Machines (DREAM) – incorporates sleep and dream-like processes within a cognitive architecture. This enables an individual robot or groups of robots to consolidate their experience into more useful and generic formats, thus improving their future ability to learn and adapt. DREAM relies on Evo- lutionary Neurodynamic ensemble methods (Fernando et al, 2012 Frontiers in Comp Neuro; Bellas et al., IEEE-TAMD, 2010) as a unifying principle for discovery, optimization, re- structuring and consolidation of knowledge. This new paradigm will make the robot more autonomous in its acquisition, organization and use of knowledge and skills just as long as they comply with the satisfaction of pre-established basic motivations. DREAM will enable robots to cope with the complexity of being an information-processing entity in domains that are open-ended both in terms of space and time. It paves the way for a new generation of robots whose existence and purpose goes far beyond the mere execution of dull tasks. http://www.robotsthatdream.eu

9.3.2. Collaborations in European Programs, except FP7 & H2020

9.3.2.1. IGLU

Title: Interactive Grounded Language Understanding (IGLU)

Programm: CHIST-ERA

Duration: October 2015 - September 2018

Coordinator: University of Sherbrooke, Canada

Partners:

University of Sherbrooke, Canada

Inria Bordeaux, France

University of Mons, Belgium

KTH Royal Institute of Technology, Sweden

University of Zaragoza, Spain

University of Lille 1 , France

University of Montreal, Canada

Inria contact: Manuel Lopes

Language is an ability that develops in young children through joint interaction with their caretakers and their physical environment. At this level, human language understanding could be referred as interpreting and expressing semantic concepts (e.g. objects, actions and relations) through what can be perceived (or inferred) from current context in the environment. Previous work in the field of artificial intelligence has failed to address the acquisition of such perceptually-grounded knowledge in virtual agents (avatars), mainly because of the lack of physical embodiment (ability to interact physically) and dialogue, communication skills (ability to interact verbally). We believe that robotic agents are more appropriate for this task, and that interaction is a so important aspect of human language learning and understanding that pragmatic knowledge (identifying or conveying intention) must be present to complement semantic knowledge. Through a developmental approach where knowledge grows in complexity while driven by multimodal experience and language interaction with a human, we propose an agent that will incorporate models of dialogues, human emotions and intentions as part of its decision-making process. This will lead anticipation and reaction not only based on its internal state (own goal and intention, perception of the environment), but also on the perceived state and intention of the human interactant. This will be possible through the development of advanced machine learning methods (combining developmental, deep and reinforcement learning) to handle large-scale multimodal inputs, besides leveraging state-of-the-art technological components involved in a language-based dialog system available within the consortium. Evaluations of learned skills and knowledge will be performed using an integrated architecture in a culinary use-case, and novel databases enabling research in grounded human language understanding will be released. IGLU will gather an interdisciplinary consortium composed of committed and experienced researchers in machine learning, neurosciences and cognitive sciences, developmental robotics, speech and language technologies, and multimodal/multimedia signal processing. We expect to have key impacts in the development of more interactive and adaptable systems sharing our environment in everyday life. http://iglu-chistera.github.io/

9.4. International Initiatives

9.4.1. Inria Associate Teams Not Involved in an Inria International Labs

9.4.1.1. NEUROCURIOSITY

Title: NeuroCuriosity

International Partner (Institution - Laboratory - Researcher):

Columbia Neuroscience (United States) - ___DEPARTMENT???___ - JACQUELINE GOTTLIEB

Start year: 2016

See also: https://flowers.inria.fr/neurocuriosity

Curiosity can be understood as a family of mechanisms that evolved to allow agents to maximize their knowledge of the useful properties of the world. In this project we will study how different internal drives of an animal, e.g. for novelty, for action, for liking, are combined to generate the rich variety of behaviors found in nature. We will approach such challenge by studying monkeys, children and by developing new computational tools.

9.4.1.2. Informal International Partners

Benjamin Clement and Manuel Lopes just begin a collaboration with Joseph Jay Williams (Harvard University), Douglas Selent and Neil Heffernan (Worcester Polytechnic Institute) to use Kidlearn algorithm and contextual multi-armed bandit to recommend explanation on ASSISTments online tutoring system. Joseph Jay Williams and Neil Heffernan used multi-armed bandit algorithm on ASSISTments platform [179] to provide efficient explanation, and new we are looking to use new algorithm to provide a more personal and relevant feedback.

Pierre-Yves Oudeyer and Didier Roy have create a collaboration with LSRO EPFL and Pr Francesco Mondada, about Robotics and education. The two teams co-organize the annual conference "Robotics and Education"in Bordeaux. Didier Roy teaches "Robotics and Education" in EPFL several times a year.

Didier Roy has created a collaboration with HEP VAud (Teachers High School) and Bernard Baumberger and Morgane Chevalier, about Robotics and education. SCientific discussions and shared professional training.

9.4.2. Participation in Other International Programs

David Filliat participates in the ITEA3 DANGUN project with Renault S.A.S. in france and partners in Korea. The purpose of the DANGUN project is to develop a Traffic Jam Pilot function with autonomous capabilities using low-cost automotive components operating in France and Korea. By incorporating low-cost advanced sensors and simplifying the vehicle designs as well as testing in different scenarios (France & Korea), a solution that is the result of technical cooperation between both countries should lead to more affordable propositions to respond to client needs in the fast moving market of intelligent mobility.

9.5. International Research Visitors

9.5.1. Visits of International Scientists

- Lauriane Rat-Fisher, IAST, Toulouse (November 23-25th)
- Fumihide Tanaka, ISI Lab, University of Tokyo, Japan (November 9th)
- Romain Brette, Institut de la Vision, Paris (February, 12th)
- Tony Belpaeme, Univ. Plymouth, UK (January)
- Tobjorn Dahl, Univ. Plymouth, UK (January)
- Jens Moenig, SAP Research, Germany (June)
- Stéphane Magnegnat, ETH Zurich, Switzerland (June)
- Francesco Mondada, EPFL, Lausanne, Switzerland Jjune)

9.5.1.1. Internships

- Yasmin Ansari, The Biorobotics Institute, Scuola Superiore S. Anna, Pontedera, Italy (January to May, 2016)

10. Dissemination

10.1. Promoting Scientific Activities

10.1.1. Scientific Events Organisation

10.1.1.1. General Chair, Scientific Chair

- PY. Oudeyer and M. Lopes have been general co-chair of Second Interdisciplinary Symposium on Information Seeking, Curiosity and Attention (Neurocuriosity 2016), London, UK (150 participants). https://goo.gl/BYL0h4
- D. Roy has been general chair of the colloquium "Robotique et Education" in Bordeaux, june 2016, http://dm1r.fr/colloque-robotique-education/.

10.1.1.2. Member of the Organizing Committees

- Manuel Lopes co-organized the R:SS 2016 workshop on Bootstrapping Manipulation Skills 06.2016 http://www.bootstrapping-manipulation.com/
- Alexander Gepperth co-organized a special session ("Incremental learning algorithms and application") on ESANN 2016, together with Barbara Hammer of Bielefled university (Germany).
- PY. Oudeyer has been member of the steering committee of the IEEE ICDL-Epirob conference.
- PY. Oudeyer has been member of the steering committee of the fOSSa conference.
- PY. Oudeyer has been "Robotics Liaison" of IJCNN 2017, Anchorage, Alaska.

10.1.2. Scientific Events Selection

10.1.2.1. Member of the Conference Program Committees

- David Filliat was Associate Editor for IROS.
- PY. Oudeyer has been member of the PC committee of IEEE ICDL-Epirob 2016.
- Alexander Gepperth was member of the program committe for IJCNN 2016, ECAI 2016 and ESANN 2016.

10.1.2.2. Reviewer

- David Filliat was reviewer for the IFAC, IV, RFIA, ICRA conferences.
- Sébastien Forestier was reviewer for IEEE ICDL-Epirob

- Manuel Lopes was reviewer for IEEE IROS, IEEE ICDL-EPIROB, IEEE ICRA, IJCAI, NIPS
- Thibaut Munzer was reviewer for IEEE IJCAI.
- Baptiste Busch reviewer for IEEE RO-MAN.
- PY. Oudeyer has been a reviewer for the conferences IEEE ICDL-Epirob and Humanoids 2016.
- Alexander Gepperth was reviewer for ESANN 2016, IJCNN2016, IEEE Symposium on Intelligent Vehicles (IV) and ECAI 2016

10.1.3. Journal

10.1.3.1. Member of the Editorial Boards

- PY. Oudeyer has been editor of IEEE CIS Newsletter on Cognitive and Developmental Systems: https://openlab-flowers.inria.fr/t/ieee-cis-newsletter-on-cognitive-and-developmental-systems/129
- PY. Oudeyer has been associate editor of IEEE Transactions on Cognitive and Developmental Systems
- PY Oudeyer has been associate editor of Robotics and Automation Letters (RA-L).
- PY. Oudeyer has been associate editor of Frontiers in Neurorobotics and Frontiers in Humanoid Robotics.
- PY. Oudeyer has been Associate editor of International Journal of Social Robotics (Springer).

10.1.3.2. Reviewer - Reviewing Activities

- David Filliat was reviewer for Journal of Intelligent Service Robotics.
- Alexander Gepperth was reviewer IEEE Transactions on Intelligent Transportation Systems
- Anna-Lisa Vollmer was reviewer for Frontiers in Robotics and AI and IEEE Transactions on Cognitive and Developmental Systems.
- PY. Oudeyer has been a reviewer for the Robotics and Automation Magazine, the Journal of Language Evolution.

10.1.4. Invited Talks

- David Filliat gave an invited presentation “Apprentissage pour les vehicules intelligents et la robotique developpementale” during the workshop “Intelligence Artificielle et Véhicule à Conduite Deleguee” organized by VEDECOM on september 28th.
- PY. Oudeyer, "Open-source art/science with Poppy Project", 15th january, Journée ECARTS, Univ. Bordeaux.
- PY. Oudeyer, "Mondes Mosaiques", Librairie Mollat, 2 février, Bordeaux.
- PY. Oudeyer, "Self-organization and active learning of language", 21 mars, Lattice, ENS Paris.
- PY. Oudeyer, "Intelligence artificielle et robotique", 21 mars, Grand Palais, Paris.
- PY. Oudeyer, "Intelligene artificielle et philosophie", 20 mai, Bordeaux.
- PY Oudeyer, "How robotic modelling can help us understand complex dynamics in development", 22 may, Views by Two keynote, International Conference on Infant Studies, New-Orleans.
- PY. Oudeyer, "Robotique éducative: les projets de l’équipe Flowers", Colloque Robotique et Education, Bordeaux.
- PY. Oudeyer, "Curiosity, exploration and learning in humans and machines", 9 july, ISSAS Summer School, Geneva, Switzerland.
- PY. Oudeyer, "How robotic modelling can help us understand complex dynamics in language and sensorimotor development", 9th september, Creativity and Evolution Summer School, Como, Italy.
- PY Oudeyer, "Comment la modélisation robotique aide à comprendre la dynamique du développement de l’enfant", 18 septembre, Colloque Biologie et Information, Cerisy, France.

- PY. Oudeyer, "Active exploration for lifelong developmental learning in humans and machines: intrinsic motivation, maturation and social guidance", 5th october, Google Deepmind seminar, London, UK.
- PY. Oudeyer, "Diverstiy of forms and developmental functions of curiosity-driven exploration", 8th october, London UK.
- PY. Oudeyer, "Intelligence artificielle et humain", Entretiens de la Cité, 5th november, Lyon, France.
- PY. Oudeyer, "Artificial intelligence and robotics: scientific, technological and societal challanges", 8th november, Académie des Technologies, Paris, France.
- PY. Oudeyer, "From fundamental research in models of human learning to educational applications", 16th november, Journée Learning Lab, Paris, France.
- PY. Oudeyer, "Diverstiy of forms and developmental functions of curiosity-driven exploration", 17th november, Journée GdR Robotique et Neuroscience, Bordeaux.
- PY. Oudeyer, "Machine learning and robotics", 5th december, Technion ConnectedWorld conference, Paris.

10.1.5. Leadership within the Scientific Community

PY. Oudeyer has been chair of IEEE Computational Intelligence Society technical committee on cognitive and developmental systems (10 task forces, 65 members); The activities of the TC are described at: https://openlab-flowers.inria.fr/t/ieee-cis-tc-on-cognitive-and-developmental-systems/41

10.1.6. Scientific Expertise

- M Lopes was expert for the EU Commission scientific programme.
- PY. Oudeyer has been an expert for the European Commission, the Polish National Research Agency, and the Swedish National Research Agency.
- PY. Oudeyer has been expert for Main à la Pâte for the textbook project “1, 2, 3: Codez!” to teach computer science in primary schools.
- PY. Oudeyer has been expert for Académie des Technologies and OPECST on artificial intelligence and its interaction with society.

10.1.7. Research Administration

PY. Oudeyer has been scientific responsible of Inria-Ensta-ParisTech EPC.

10.2. Teaching - Supervision - Juries

10.2.1. Teaching

Master: Robotique Developmental et Cognitive, 35 heures, Nantes, (Manuel Lopes et PY Oudeyer)

Master: Robotique Developmental et Cognitive, 35 heures, Universite de Bordeaux, (Manuel Lopes et PY Oudeyer)

License: Inteligencia Artificial, 90 heures, Instituto Superior Tecnico, Lisboa, (Manuel Lopes)

License: Introduction to Matlab, 21 heures. L3, ENSTA - ParisTech (David Filliat).

Master: Robotique Mobile, 21 heures. M2, ENSTA - ParisTech (David Filliat).

Master: Perception pour la Robotique, 6 heures. M2, ENSTA - ParisTech (David Filliat).

Master: Perception pour la robotique, 12 heures. M2 Systemes Avances et Robotique, University Pierre et Marie Curie (David Filliat)

Master: Perception pour la Robotique Développementale, 3 hours, CogMaster (David Filliat)

Licence Informatique, 64h Bordeaux University (Sébastien Forestier)

PY. Oudeyer taught a course on "Robotic modelling of cognitive development" at ENS Rennes, 12 h

PY. Oudeyer taught a course on "Robotic modelling of cognitive development" at Enseirb, 2 h

PY. Oudeyer taught a course on "Robotic modelling of cognitive development" at CogMaster, Paris, 3 h

PY. Oudeyer taught a course on "Developmental and cognitive robotics" at Univ. Mons, Belgium, 3h

PY. Oudeyer coordinated the project Poppy Education, which has developped several educational robotics kits for computer science education in high-schools

Continuing education: Robotics for education, 30 h, EPFL (Didier Roy)

10.2.2. Supervision

PhD in progress: Sébastien Forestier, Models of curiosity-driven learning of tool use and speech development, started in sept. 2015 (superv. P-Y. Oudeyer)

PhD in progress: William Schueller, Study of the impact of active learning and teaching in naming games dynamics, started in sept. 2015 (superv. P-Y. Oudeyer)

PhD in progress: Alvaro Ovalle-Castaneda, Computational models of intrinsically motivated learning and exploraiton, started in oct. 2016 (superv. P-Y. Oudeyer)

PhD in progress: Thibault Desprez, Design and study of the impact of educational robotic kits in computer science education, started in dec. 2016 (superv. P-Y. Oudeyer)

PY. Oudeyer supervised three master thesis internship: Thibault Desprez (M2, educational robotics), Marie Demangeat (M2, educational robotics), Sébastien Mick (M2, design and study of robotic prosthesis)

PY. Oudeyer supervised a team of computer and pedagogical engineers and researchers for the project Poppy Education (Didier Roy, Stéphanie Noirpoudre, Théo Segonds, Damien Caselli, Nicolas Rabault, Matthieu Lapeure)

PhD in progress: Thomas Hecht, Bio-inspired sensor fusion, started November 2013 (superv. Alexander Gepperth).

PhD : Egor Sattarov, Multimodal vehicle perception architecture, Université Paris-Saclay, 9/12/2016 (co-superv. Alexander Gepperth).

PhD : Thomas Kopinski, Machine Learning for human-machine interaction, Université Paris-Saclay, ENSTA ParisTech, 12/02/2016 (superv. Alexander Gepperth).

PhD in progress: Benjamin Clement, Intelligent Tutoring Systems, started oct 2015 (superv. Manuel Lopes and Pierre-Yves Oudeyer).

PhD in progress: Thibaut Munzer, Learning from Instruction, started oct 2013 (superv. Manuel Lopes).

PhD in progress: Baptiste Busch, Interactive Learning, started oct 2014 (superv. Manuel Lopes).

PhD in progress: Alexandra Delmas, Auto-Apprentissage Auto-Adaptable pour la compliance au traitement, started oct 2014 (superv. Manuel Lopes).

PhD : Alexandre Armand, Situation Understanding and Risk Assessment Framework for Preventive Driver Assistance, Université Paris-Saclay, ENSTA ParisTech, 31/05/2016, superv. David Filliat, Javier Ibanez-Guzmann

PhD in progress: Yuxin Chen, Interactive learning of objects and names on a humanoid robot, started oct. 2013 (superv. David Filliat).

PhD in progress: Celine Craye, Curiosity and visual attention for the guidance of an exploration robot, started apr. 2014 (superv. David Filliat).

PhD in progress: Adrien Matricon : Task dependent visual feature selection for optimising and generalizing robotics skills (superv. David Filliat, Pierre-Yves Oudeyer).

PhD in progress: José Magno Mendes Filho, Planning and control of an autonomous AGV in environment shared with humans, started Oct. 2015 (superv. David Filliat and Eric Lucet (CEA))

PhD in progress: Joris Guery, Domain adaptation for visual object recognition, started Oct. 2014 (superv. David Filliat and Bertrand Le Saulx (ONERA))

HdR :Alexander Gepperth, New learning paradigms for real-world environment perception, université Pièrre et Marie Curie, 27/6/2016

10.2.3. Juries

Manuel Lopes was in the jury of Ben-Manson Toussaint (2016), Modeling Perceptual-Gestural Knowledge for Intelligent Tutoring Systems, supervised by Vanda Luengo, University of Grenoble, France

David Filliat was in the jury of Isabelle Leang (15/12/2016, Rapporteur) : Fusion en ligne d'algorithmes de suivi visuel d'objet

David Filliat was in the jury of Egor Sattarov (09/12/2016, Examinateur) : Etude et quantification de la contribution des systèmes de perception multimodale assistés par des informations de contexte pour la détection et le suivi d'objets dynamiques

Alexander Gepperth was in the jury of Egor Sattarov (09/12/2016, Examinateur) : Etude et quantification de la contribution des systèmes de perception multimodale assistés par des informations de contexte pour la détection et le suivi d'objets dynamiques

Alexander Gepperth was in the jury of Thomas Kopinski (12/2/2016, Examinateur) : Machine learning method for human-machine interaction

David Filliat was in the jury of Fabrice Mayran de Chamiso (18/11/2016, Examinateur) : Navigation exploratoire au long de la vie une approche intégrant planification, navigation, cartographie et localisation pour des robots mobiles disposant de ressources finies

David Filliat was in the jury of Chunlei Yu (15/09/2016, Examinateur) : Contribution to evidential models for perception grids Application to intelligent vehicle navigation

David Filliat was in the jury of Hendry Ferreira Chame (10/01/2016, Rapporteur) : Egocentric Representations for Autonomous Navigation of Humanoid Robots

PY. Oudeyer was a member of the PhD juries of Maxime Carrere (Combiner les apprentissages motivés et associatifs, Univ. Bordeaux), Remi Fresnoy (Modélisation de l'activité gestuelle et sélection automatique de feedback pour des environnements interactifs d'apprentissage : application à la calligraphie, UTC Compiègne), Raphaël Rose-Andrieux (Modèle probabiliste hiérarchique de la locomotion bipède).

PY. Oudeyer was a member of the HdR of Alexander Gepperth, "New learning paradigms for real-world environment perception", Ensta ParisTech, Paris.

PY. Oudeyer was a member of the jury for selecting ENS Rennes (France) PhD grants.

10.3. Popularization

10.3.1. Poppy Education

10.3.1.1. Events participation

January 2016, Observation Sequence for students from middle-school (Inria Bordeaux Sud-Ouest): S. Noirpoudre, T. Desprez, M. Demangeat, T. Laine) - We welcomed 5 students from middle-school (14 years old) during a week to discover the working environment and to introduce them to robotics

January 2016, Robot makers'day (Talence): S. Noirpoudre, D. Caselli, T. Desprez - Exhibition stand to show the projet Poppy Education and Poppy robots

January 2016, Training day at Espe de Bordeaux (Ecole supérieure du professorat et de l'éducation): D. Roy, S. Noirpoudre, T. Desprez, M. Demangeat) - Train a group of teachers initiate in programmation with the language visual Snap! and to robotics with Poppy Ergo Jr)

January 2016, Robots day (Multimedia library of Talence): P. Rouanet, T. Segonds - Programming workshop with Poppy torso robot

January 2016, Robots day (Multimedia library of Talence): P. Rouanet - A talk to present the platform robotics Poppy through science, art and education.

January 2016, Symposium Didastic-Didapro (Namur): D. Roy - Talk to present Poppy Education

January 2016, Eidos 2016 event (Dax): S. Noirpoudre - A talk to present Poppy Education

March 2016, Education exhibition Educatice-Educatec (Paris) : S. Noirpoudre, D. Roy - Exhinibition stand to present the robotics platforme Poppy and the use in Education (Poppy Education)

March 2016, Training day at Espe de Bordeaux (Ecole supérieure du professorat et de l'éducation): T. Desprez - Train a group of teachers in Snap!

March 2016, SNCEEL (organisation professionnelle de chefs d'établissement d'enseignement libre), Journées Collèges event (Paris), T. Desprez - Talk to present Poppy project and the pedagogical activities

April 2016, Connect thouars event (Talence): T. Desprez, S. Noirpoudre, M. Demangeat - Exhibition stand to present the project Poppy Education and workshop animation for kids (programming of Ergo in Snap!)

April 2016, Rob'o d'Evian: D. Roy (Evian) - Talk to present Poppy Education

May 2016, Robotics and Education days (ENS Lyon): D. Roy, S. Noirpoudre - Talk to present Poppy project and the pedagogical activities

May 2016, Bordeaux Geek Festival (Bordeaux): M. Demangeat, T. Desprez - Exhibition stand to show/present the robotics platform Poppy

May 2016, Forum des Nouvelles Initiatives de Médiation Scientifique (Bordeaux): D. Roy - Talk to present the project Poppy Education

May 2016, Forum des Nouvelles Initiatives de Médiation Scientifique (Bordeaux): T. Desprez, S. Noirpoudre - Exhibition stand to present the project Poppy Education and show the robots (real demonstrations) and pedagogical activities

May 2016, Visit of teachers of Espe Aquitaine (Inria - Bordeaux Surd-Ouest): S. Noirpoudre, D. Roy - Visit of the research center and presentation of Poppy Education project and to the robotic kits (25 teachers)

June 2016, Symposium Education and Robotics (Talence): D. Roy, T. Desprez - Talk to present Poppy Education project (purpose, pedagogical activities and the results)

June 2016, Symposium Education and Robotics (Talence): S. Noirpoudre - Exhibition stand to show Poppy Education project (demonstrations)

August 2016, Université d'été Ludovia (Ax-les-Thermes): P. Rouanet, M. Demangeat - Exhibition stand Poppy Education during 3 days in partnership with l'Académie de Bordeaux

August 2016, Université d'été Ludovia (Ax-les-Thermes): D. Roy, P. Rouanet, M. Demangeat - Workshop / presentation / demonstration of Poppy Education as part of the ExplorCamps.

October 2016, Coding Pi Science Day (CERN close to Geneva): S. Noirpoudre, T. Segonds - Conference to present the pedagogical robotic kit Poppy Ergo Jr

October 2016, Coding Pi Science Day (CERN close to Geneva): S. Noirpoudre, T. Segonds - Robotics workshop, one day to build and program a robot (30 participants)

October 2016, Fête de la science (Inria Bordeaux Sud-Ouest): S. Noirpoudre - 8 programming workshop in 2 days (with middle school students) using Snap! and the robot Poppy Ergo Jr

November 2016, Erasmus project "ICT WORLD : Imaging, Coding, Transforming and Modeling the World" (Inria Bordeaux Sud-Ouest): S. Noirpoudre, programming workshop using Snap! and the robot Poppy Ergo Jr (35 students and 14 teachers)

Novembre 2016, Inria Learning Lab (Paris): D. Roy - Presentation of Poppy Education

December 2016, Observation Sequence for Grade 3 Students (Inria Bordeaux Sud-Ouest): S. Noirpoudre, T. Desprez) - We welcomed 2 students from middle-school during a week to discover the working environment and to introduce them to robotics

10.3.1.2. Training and meeting

- January 2016, Meeting with teachers partners of the Poppy Education: Poppy Education project team - Talking about pedagogical activities and robots availabilities
- March 2016, Meeting with teachers partners of Poppy Education, Poppy Education project Team - Feedback and presentations on pedagogical activities and the use of robots in the classroom
- May 2016, Meeting with teachers partners of Poppy Education, Poppy Education project team - Feedback on pedagogical activities and the use of robots in the classroom
- May 2016, Train Inria workers (from scientific mediation), S. Noirpoudre - Learn how to present the Poppy project
- June 2016, Train Canope 33 workers, S. Noirpoudre - Programming the robot Ergo Jr using Snap!
- October 2016, Meeting with teachers partners of the Poppy Education project: Poppy Education project team - Presentation of the progress of the year and presentations of pedagogical activities
- November 2016, Train new teachers partners of Poppy Education: S. Noirpoudre - Building and programming the robot Poppy Ergo Jr

10.3.2. Inirobot

10.3.2.1. Events participation

January 2016, Training day at Espe de Bordeaux (Ecole supérieure du professorat et de l’éducation): D. Roy, S. Noirpoudre, T. Desprez, M. Demangeat) - Train a group of teachers initiate in programmation with the Inirobot kit.

January 2016, Symposium Didastic-Didapro (Namur): D. Roy - Talk to present Inirobot kit.

March 2016, Education exhibition Educatice-Educatec (Paris) : S. Noirpoudre, D. Roy - Exhinibition stand to present the robotics kit Inirobot.

March 2016, SNCEEL (organisation professionnelle de chefs d’établissement d’enseignement libre), Journées Collèges event (Paris), T. Desprez - Talk to present Inirobot kit.

April 2016, Rob’o d’Evian: D. Roy (Evian) - Talk to present Inirobot kit.

May 2016, Robotics and Education days (ENS Lyon): D. Roy, S. Noirpoudre - Talk to present Inirobot kit.

May 2016, Forum des Nouvelles Initiatives de Médiation Scientifique (Bordeaux): D. Roy - Talk to present inirobot kit.

June 2016, Symposium Education and Robotics (Talence): D. Roy - Talk to present Inirobot kit.

August 2016, Université d’été Ludovia (Ax-les-Thermes): P. Rouanet, M. Demangeat - Exhibition stand Inirobot during 3 days in partnership with l’Académie de Bordeaux

August 2016, Université d’été Ludovia (Ax-les-Thermes): D. Roy, P. Rouanet - Workshop / presentation / demonstration of Inirobot kit as part of the ExplorCamps.

August 2016, Université d’été Ludovia (Ax-les-Thermes): D. Roy wins Ludovia Prize. http://ludovia.org/2016/coups-de-coeur-de-ludovia/

September 2016, Colloque sur les contenus périscolaires (Artigues-près-Bordeaux): D. Roy - inirobot (organized by Senator Françoise Cartron)

October 2016, Journées APMEP (Lyon): J. Rivet, G. Lassus, members of Poppy Education teachers team - workshops on Inirobot and Poppy Education, organized by D. Roy

October 2016, Journées APMEP (Lyon): D. Roy wins Hoquenghem Prize. https://www.inria.fr/centre/bordeaux/actualites/didier-roy-recoit-le-prix-serge-hocquenghem

Novembre 2016, Inria Learning Lab (Paris): D. Roy - Presentation of Inirobot kit.

10.3.2.2. Training and meeting

- Février 2016, French Senat (Paris), audition by Senator Françoise Cartron for educational activities : D. Roy - presentation / demonstration of Inirobot kit .
- October 2016, Robotics for education Training week "Graines de sciences": D. Roy (Fondation "La Main à la Pâte", Marseille CIRM)

10.3.3. KidBreath

February 11th 2016, 2nd Meeting for Aquitaine and Euskadi companies in Biology and Health: A. Delmas - Poster presentation of KidBreath project.

September 16th to 18th 2016, Hackathon of innovation in pulmonary diseases Respirhacktion: A. Delmas - Oral presentation and project development in hackathon.

October 5th to 7th 2016, 5th Conference in Health Ergonomics and Patient Safety: A. Delmas - Poster presentation of KidBreath project [102],

November 16th 2016, Learning Lab day: A. Delmas, B. Clément, P-Y. Oudeyer, D. Roy - Oral presentation of Flowers projects linked to Education.

December 2nd to 3rd 2016, 5th edition of Serious Games in Medicine Conference: A. Delmas - Oral presentation of KidBreath project

10.3.4. Other

PY Oudeyer wrote popular science articles about computer science, artificial intelligence and robotics, and gave several interviews in the general press and at radio and TV programs: see http://www.pyoudeyer.com/popular-science/ and http://www.pyoudeyer.com/press/ and has been maintaining a youtube channel showing popular science videos https://www.youtube.com/channel/UC7QuDF8AaE6mqEM9W_S30RA/featured

D. Roy is co-organiser of R2T2 International Mission with EPFL and ESPE Martinique: Remote Robotics programming with children. https://www.thymio.org/en:thymio-r2t2

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