

INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

# **Project-Team Flowers**

# Flowing Epigenetic Robots and Systems : Developmental and Social Robotics

Bordeaux - Sud-Ouest



# **Table of contents**

1.	Теат	1
2.	Overall Objectives	1
	2.1. Introduction	1
	2.2. Highlights of the year	2
3.	Scientific Foundations	2
	3.1.1. Internal guiding mechanisms.	4
	3.1.2. Socially guided learning.	4
4.	Application Domains	4
5.	Software	5
	5.1. The Exploration Explorer	5
	5.2. UFlow	7
	5.3. B2dSim Simulator	8
	5.4. ShowMe for TabletPC	8
	5.5. iShow	8
6.	New Results	
	6.1. Evaluation of intrinsic motivation systems as active learning	9
	6.2. Conceptualization and formalization of the landscape of intrinsic motivation systems	9
	6.3. New algorithms for intrinsically motivated exploration	10
	6.4. Stable kernels and fluid body envelopes	10
	6.5. Learning the informational topology in robotic body maps.	10
	6.6. Developmental exploration in models of the formation of shared ontologies in a population	of
	agents.	11
	6.7. Intuitive gestural interfaces for human-robot language teaching	11
7.	Contracts and Grants with Industry	
8.	Other Grants and Activities	
9.	Dissemination	
	9.1. Animation of the scientific community	12
	9.1.1. Editorial boards	12
	9.1.2. Program Committees	12
	9.1.3. Reviews	12
	9.1.4. Other	13
	9.2. Invited talks	13
	9.3. Teaching	13
	9.4. Communication towards the general public	13
10.	Bibliography	.13

# 1. Team

#### **Research Scientist**

Pierre-Yves Oudeyer [ INRIA, Team Leader, Research Associate (CR) ]

#### **Technical Staff**

Jérome Béchu [ Associate Engineer, since Oct. 2008 ]

#### **PhD Student**

Adrien Baranès [ INRIA, CORDI/S, since Oct. 2008 ] Pierre Rouanet [ INRIA, CORDI/C, since Oct. 2008 ]

#### Administrative Assistant

Marie Sanchez [ INRIA ]

Other

Frederic Delaunay [ INRIA, Internship, Ecole Normale Supérieure de Cachan, Magistère d'informatique ] Thomas Schatz [ INRIA, Internship, University Paris 6 (ISIR), Master 2 Robotique ]

# 2. Overall Objectives

# 2.1. Introduction

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 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.

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;
- 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 three axis:

- Intrinsically motivated exploration and 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 also studied as active learning mechanisms, allowing to learn efficiently in large inhomogeneous sensorimotor spaces;
- 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:** FLOW-ERS studies mechanisms that allow a robot to infer structural information out of sets of sensorimotor channels whose semantics is unknown, such as for example the topology of the body and the sensorimotor contingencies (propriocetive, visual and acoustic).

These three research axis are applied to the learning of two kinds of skills: basic sensorimotor skills and basic socio-linguistic skills (bootstrapping and learning of the first words).

## 2.2. Highlights of the year

The FLOWERS team was created in April, as a support for the action exploratoire awarded to Pierre-Yves Oudeyer.

Together with partners from ISIR, Paris and ENSTA, Paris, Pierre-Yves Oudeyer wrote a project proposal for the European ICub Call and were ranked 2nd out of 31 and obtained an ICub humanoid robot.

Pierre-Yves Oudeyer was invited at College de France, for the Colloque de rentrée, to present work on computational modelling of language formation and evolution (link).

Pierre-Yves Oudeyer was nominated Editor of the IEEE CIS Newsletter on Autonomous Mental Development, which is an important publication for the animation of the developmental/epigenetic robotics community.

# 3. Scientific Foundations

## 3.1. Scientific Foundations

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, such as 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 makes 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 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" [60]. 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 [39], 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 [45] [62]. The approach of developmental robotics consists in importing and implementing concepts and mechanisms from developmental psychology [47], cognitive linguistics [30], and developmental cognitive neuroscience [42] 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 [26], grounding [37], situatedness [18], self-organization [58], enaction [61], and incremental learning [28].

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. 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 [1]. 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:

Psychologists have identified two broad classes of guiding mechanisms which control exploration:

- 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 on-line active self-regulation of the growth of complexity in learning situations;
- 2. **social learning and guidance,** which exists in many different forms like emotional reinforcement 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 [47], 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. Development is 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" [19] [34]. 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 [22] [31] [33]. 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 behaviors and curiosity [32] [40] [55]. Based on this, a number of researchers have began in the past few years to build computational implementation of intrinsic motivation [1][2] [53] [21] [41] [46] [54]. 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 [2][1] [49] . Specific and complex problems are posed by real sensorimotor spaces, in particular due to the fact that they are deeply inhomogeneous: for example, some regions of the space are often unlearnable due to inherent stochasticity or difficulty. In such cases, heuristics based on the incentive to explore zones of maximal unpredictability or uncertainty, which are often used in the field of active learning [29] [38] typically lead to catastrophic results. In FLOWERS, we aim at developing intrinsically motivated exploration mechanisms that scale in those spaces.

#### 3.1.2. Socially guided learning.

Social guidance is as important as intrinsic motivation in the cognitive development of human babies [47]. There is a vast literature on mechanisms allowing a human to socially guide a robot towards the learning of new sensorimotor skills [52]. Yet, many existing experiments focus either on only intrinsically motivated exploration [1] [21], or only socially guided exploration with imitation, demonstration or social cheering [27] [20]. Only few attempts, such as in [59], have been tried to couple intrinsic motivation and social learning. In FLOWERS, we work on developing advanced mechanisms for coupling social learning and state-of-the-art intrinsic motivation systems.

# 4. Application Domains

## 4.1. Application Domains

• **Personal 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 aging

society. For example, UNECE evaluates that the industry of entertainment, personal and service robotics will grow from \$5.4Bn to \$17.1Bn over 2008-2010. Yet, to realize this vision, important obstacles need to be overcome: these robots will have to evolve in unpredictable homes and learn new skills 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.

• Video games. In conjunction with entertainment robotics, a new kind of video games are developing in which the player must either take care of a digital creature (e.g. Neopets), or tame it (e.g. Nintendogs), or raise/accompany them (e.g. Sims). The challenges entailed by programming these creatures share many features with programming personal/entertainment robots. Hence, the video game industry is also a natural field of application for FLOWERS.

# 5. Software

## 5.1. The Exploration Explorer

Participants: Adrien Baranès [correspondant], Pierre-Yves Oudeyer.

The Exploration Explorer is a Matlab toolbox designed to allow the evaluation and systematic comparison of various intrinsically motivated exploration algorithms. It includes both a graphical interface for choosing the particular exploration algorithm among several possible ones, as well as the underlying low-level prediction systems, for tuning their parameters, and for choosing the sensorimotor space to be used for evaluation. Several algorithms are currently implemented, including different variants of the IAC algorithm [1]. Several default sensorimotor spaces, together with their visualizations, are included (see Figure 2). The toolbox also includes modules to visualize both in realtime and as postprocessing the evolution of performances of each algorithm (see Figure 3). In the mid-term, this system aims to be distributed publicly as open source.

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Figure 1. Matlab Interface of the Exploration Explorer

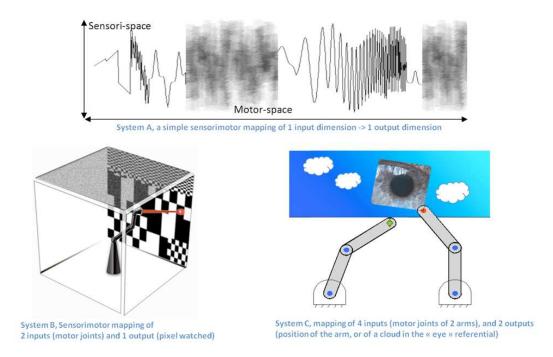
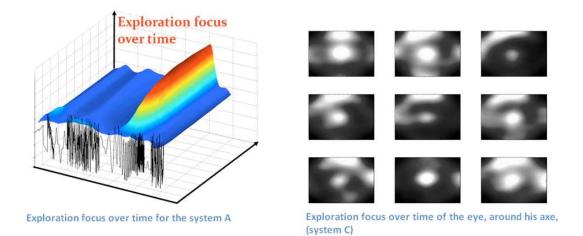


Figure 2. Several sensorimotor spaces, including modules for their visualization, are included in the Exploration Explorer



*Figure 3. Advanced visualization tools for monitoring the exploration algorithm properties are included in the toolbox.* 

## **5.2. UFlow**

Participants: Jérome Béchu [correspondant], Pierre-Yves Oudeyer.

The UFlow Toolbox is a collection of various software modules for programming and scripting robot sensorimotor loops, aimed at allowing rapid prototyping in the FLOWERS team, and integrated in the URBI framework. URBI, developed by GOSTAI, supports the integration of heterogeneous robotic software modules. It uses a dynamic scripting language, witch manage parallel and event processing. Each module, called UObject, is written in C++.

Currently we have developed two UObjects for image acquisition and access: uNetCam and uOcvCam. uNetCam Manages a pan/tilt ethernet camera, this module connect to the camera ip, and acquires image in a streaming flow (accurency 10 fps). We can control in real-time using UrbiScript the pan/tilt movement. The second module to acquire image is uOcvCam. This uobject is use to get image from usb default camera device.

An UObject, named UBlob, analyses a image and detects a color blob's position in real-time. To realise this analyse, we have two options, rgb or YCbCr detection. In both, the user have to specify the range of each composant to create a filter.

The figure 4 presents the UGui UObject. This component is a graphical interface for Urbi, allowing to manipulate and animate easily graphical forms and superimpose them on other images such as images from the camera.

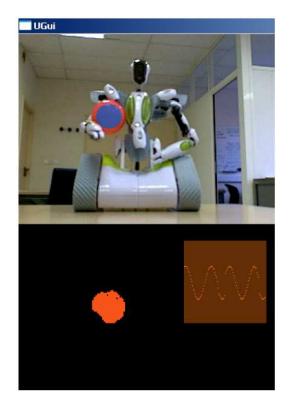


Figure 4. This component is a graphical interface for Urbi, allowing to manipulate and animate easily graphical forms and superimpose them on other images such as images from the camera.

Finally, the last UObject developed (in progress) is USpeechAnalysis. This composant is designed to extract in real-time MFCC, Pitch and Intensity from the audio input of computer.

## 5.3. B2dSim Simulator

Participants: Frédéric Delaunay [correspondant], Pierre-Yves Oudeyer.

B2dSim is a 2D physical simulation environment built to be used in simulated motor learning experiments. It is built in JAVA, based on the box2D software library, and has a client server architecture, coupled with an embedded scripting language, which allows the user to build motor learning software algorithms in other languages, such as Matlab or C++. B2dSim Simulator is publicly available here.

### **5.4. ShowMe for TabletPC**

Participants: Pierre Rouanet [correspondant], Pierre-Yves Oudeyer.

It has been built on a TabletPC in order to allow mobility during the interaction. By looking at the screen, the user can see what the robot is looking at. He can also drive the robot by sketching on the touch-screen using the stylus. Then, specific gestures are used to draw the attention of the robot towards new objects, and the software allows the user to associate a name to these objects. Finally, the software allows the user to ask the robot to search and reach an object given its name/the word associated to it.

ShowMe is a tablet PC application that facilitates intuitive and robust human-robot teaching interactions.

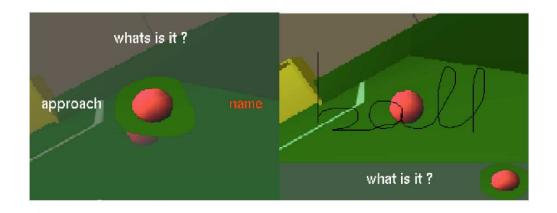


Figure 5. ShowMe is a software designed to make the interaction between a human and a robot much easier, and more particularly to help the user to show and learn new objects to the robot.

# 5.5. iShow

Participants: Pierre Rouanet [correspondant], Pierre-Yves Oudeyer.

ShowMe has been ported to iPhone in order to use its multiple-interaction and multi-touch abilities and with the mid-term aim of making the software available to a larger audience. Besides the TabletPC version features (see section 5.4), this versions provides several new functionalities, such as driving the robot by litterally using the iPhone as a steering wheel (with the accelerometer). The interface has been re-designed based on iPhone API, making it much simpler and easy to use. The stylus handwriting has been replaced by the iPhone virtual keyboard, making the word recognition trivial.

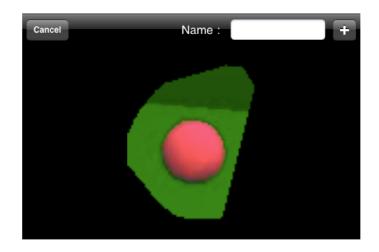


Figure 6. iShow is an iPhone application that facilitates intuitive and robust human-robot teaching interactions

# 6. New Results

## 6.1. Evaluation of intrinsic motivation systems as active learning

Participants: Adrien Baranès, Pierre-Yves Oudeyer.

Developmental robots have a sharp need for mechanisms that may drive and self-organize the exploration of new skills, as well as identify and organize useful sub-spaces in its complex sensorimotor experiences. In psychology terms, this amount to trying to answer the question "What is interesting for a curious brain?". Among the various trends of research which have approached this question, of particular interest is work on intrinsic motivation. Intrinsic motivations are mechanisms that guide curiosity-driven exploration, that were initially studied in psychology [63] [23] [33] and are now also being approached in neuroscience [32] [51] [56]. They have been proposed to be crucial for self-organizing developmental trajectories [1] as well as for guiding the learning of general and reusable skills (Barto et al., 2005). Experiments have been conducted in real-world robotic setups, such as in [1] where an intrinsic motivation system was shown to allow for the progressive discovery of skills of increasing complexity, such as reaching, biting and simple vocal imitation with and AIBO robot. In these experiments, the focus was on the study of how developmental stages could selforganize into a developmental trajectory without a direct pre-specification of these stages and their number. Yet, these algorithms can also be considered as "active learning" algorithms. This year, we have shown that some of them also allow for very efficient learning in the unprepared spaces with the typical properties of those encountered by developmental robots, outperforming standard active learning heuristics. These results were partly published in [11][12].

Other publications are under preparation.

# 6.2. Conceptualization and formalization of the landscape of intrinsic motivation systems

Participants: Pierre-Yves Oudeyer, Frédéric Kaplan.

Intrinsic motivation is a crucial mechanism for open-ended cognitive development since it is the driver of spontaneous exploration and curiosity. Yet, it has so far only been conceptualized in ad hoc manners in the epigenetic robotics community. We have this year put effort on reviewing different approaches to intrinsic motivation in psychology and connecting them to the issues that are considered important in developmental robotics. Furthermore, we have proposed a unified definition of intrinsic motivation, based on the theory of Daniel Berlyne. Based on this definition, we have formalized a landscape of types of computational approaches, making it possible to position existing and future models relative to each other, and we have shown that important approaches are still to be explored. This work has been published in [49][14].

## 6.3. New algorithms for intrinsically motivated exploration

Participants: Adrien Baranès, Pierre-Yves Oudeyer.

Based on the formal landscape described in the previous paragraph, a subspace of variants of knowledgebased predictive intrinsic motivation systems was investigated and systematically compared both based on measures of the self-organization of developmental trajectory and on measures of the efficiency of learning in simulated robotic sensorimotor spaces. Based on these systematic evaluations and comparisons, a new version of the Intelligent Adaptive Curiosity algorithm (IAC) have been developed which clearly outperforms the one described in [1]. It was tested in complicated simulated multi-arm forward model learning in robots and was shown to outperform random exploration, standard active learning heuristics, and previous version of IAC. The systematic studies of basic variants was presented in [15].

Publications on the new IAC algorithm are under writing.

#### 6.4. Stable kernels and fluid body envelopes

Participants: Frédéric Kaplan, Pierre-Yves Oudeyer.

This work is mainly philosophical and consists in studying how work in developmental robotics can foster a shift in the conceptions of the self, of the body, and of individuation. Recent advances in robotics lead us to consider, on the one hand, the notion of a kernel, a set of stable algorithms that drive developmental dynamics and, on the other hand, variable body envelopes that change over time. This division reverses the classic notion of a fixed body on which different software can be applied to consider a fixed software that can be applied to different kinds of embodiment. Thus, it becomes possible to study how a particular embodiment shapes developmental trajectories in specific ways. It also leads us to a novel view of the development of skills, from sensorimotor dexterity to abstract thought, based on the notion of a fluid body in continuous redefinition. This work was published in [9][10].

## 6.5. Learning the informational topology in robotic body maps.

Participants: Thomas Schatz, Pierre-Yves Oudeyer.

In developmental robotics [45], one aims at building robot capable of learning progressively and continuously new skills in unknown changing bodies and environments. In particular, this involves mechanisms for discovering its own body and its relationships with the environment. In this context, learning body maps is a crucial challenge. Body maps are topological models of the relationships among body sensors and effectors, which human children learn progressively, abstract and build upon to learn higher-level skills involving the relationships between the shape of the body and the physical environment [36]. Accordingly, inferring and reusing body maps from initially uninterpreted sensors and effectors has been identified as an important objective in developmental robotics [50]. Several authors [48] have proposed an approach based on information theory and dimensionality reduction to infer the topology of the body. Based on this approach, we have extended the method to allow its applicability to dynamically reconfigurable bodies, and proposed extensions that allow to re-use these body maps to control reconfigurable bodies. This work is described in [17].

Further technical publications are under way.

# 6.6. Developmental exploration in models of the formation of shared ontologies in a population of agents.

Participants: Frédéric Delaunay, Pierre-Yves Oudeyer.

We have studied how developmental mechanisms can impact importantly the efficiency of cultural evolution dynamics in the formation of shared lexicons. Thus, this work tries to gather two threads of research: semiotic dynamics and developmental sciences.

On the one hand, many models of language formation and self-organization were developed in the last decade, under the general theoretical umbrella of semiotic dynamics [57]. One of the best studied model is the naming game [44], in which a population of agents builds a shared lexicon, associating words and meanings, through cultural evolution and self-organization. In these simulations, agents interact in a peer-to-peer manner, negotiating each time the word that shall be associated to a randomly chosen meaning. Experiments have shown that simple feedback mechanisms lead to the self-organization of a globally shared set of associations [44] [57].

On the other hand, recent years have also seen the multiplication of models showing that a developmental approach to learning can be very efficient in real-world spaces. The general idea is based on the gradual control of the complexity of the task or skill to be learnt, "starting simple" and progressively becoming more complicated. This can be realized through the control of the number of degrees of freedom of the motor apparatus, the sensitivity of sensors, or the complexity of the learning situations, which are progressively and actively increased [1] [24] [34].

Based in these two strands of research combined, we showed that the introduction of active mechanisms of complexity control at the level of individuals in naming game experiments allows to drastically improve the speed of convergence of the global population to a shared lexicon. This was presented in [13].

Further more technical publications are under way.

## 6.7. Intuitive gestural interfaces for human-robot language teaching

Participants: Pierre Rouanet, Pierre-Yves Oudeyer.

Social robots are drawing an increasing amount of interest both in scientific and economic communities [35] [25]. These robots should typically be able to interact naturally and intuitively with non-engineer humans, in the context of domestic services or entertainment. Yet, an important obstacle needs to be passed: providing robots with the capacity to adapt to novel and changing environments and tasks, in particular when interacting with non-engineer humans. One of the important difficulties is related to mutual perception and joint attention [43]. For example, when one has to teach a novel word or a new command to a robot, several challenges arise:

- 1. Attention drawing: when needed the human shall be able to draw the attention of the robot towards himself and towards the interaction (i.e. the robot should stop its activities and pay attention to the human);
- 2. Pointing: once the robot is concentrated on the interaction, the human should be able to show a part of the environment (typically an object) he is thinking of to the robot, typically by pointing, in order to establish a form of joint attention;
- 3. Naming: the human should be able to introduce a symbolic form that the robot can detect, register and recognize later on;

Given that users are not engineers, this should be realized both in a very intuitive and very robust manner in completely uncontrolled environments. This implies that relying on traditional vision techniques for detecting and interpreting natural human pointing gestures, and on traditional speech recognition techniques for spotting and recognizing (potentially new) words will not work. One way to achieve intuitive and robust attention drawing, pointing and naming is to develop simple artefacts that will serve as mediators between the man and the robot to enable natural communication, in much the same way as icon based artefacts were developed for leveraging natural linguistic communication between man and bonobos (see Kanzi and Savage-Rumbaugh).

This year, we have began to experiment the development of such artefacts and associated interaction techniques, and evaluate them. These interaction techniques are based on gestural interaction through a portable touch screen that serves the role of mediator between the human and the robot. More information is available in [16].

More details publications are under way.

# 7. Contracts and Grants with Industry

# 7.1. Contracts and Grants with Industry

Contacts have been established with various companies and joint project proposals are under review.

# 8. Other Grants and Activities

## 8.1. Other Grants and Activities

Pierre-Yves Oudeyer obtained an "action exploratoire" INRIA grant of 120 Keuros, which allowed to recruit Adrien Baranes for a PhD.

Pierre-Yves Oudeyer obtained an ADT INRIA grant which allowed to recruit Jerome Bechu as a CDD engineer.

Pierre-Yves Oudeyer obtained a Région Aquitaine grant of 120 Keuros which allowed to recruit Pierre Rouanet as a PhD student.

# 9. Dissemination

## 9.1. Animation of the scientific community

#### 9.1.1. Editorial boards

Pierre-Yves Oudeyer has worked as Editor of the IEEE CIS AMD Newsletter, and member of the IEEE CIS Technical Committee on Autonomous Mental Development.

Pierre-Yves Oudeyer has worked as Associate Editor of: Frontiers in Neurorobotics (Frontiers Foundation) and International Journal of Social Robotics (Springer).

#### 9.1.2. Program Committees

Pierre-Yves Oudeyer was a member of the following program committees: IEEE Congress on Evolutionary Computation (IEEE CEC'09), 2009; IEEE Alife 2009; ABiALS 2008: The fourth workshop on Anticipatory Behavior in Adaptive Learning Systems; International Conference on Intelligent Virtual Agents (IVA'08); Artificial Life XI Conference, 2008; International Conference on Epigenetic Robotics, 2008.

#### 9.1.3. Reviews

Pierre-Yves Oudeyer reviewed papers for the journals: Interaction Studies, International Journal of Social Robotics, Adaptive Behavior, Connection Science, Artificial Life, and for the conferences: IEEE Congress on Evolutionary Computation (IEEE CEC'09), 2009; IEEE Alife 2009; ABiALS 2008: The fourth workshop on Anticipatory Behavior in Adaptive Learning Systems; International Conference on Intelligent Virtual Agents (IVA'08); Artificial Life XI Conference, 2008; International Conference on Epigenetic Robotics, 2008.

#### 9.1.4. Other

Pierre-Yves Oudeyer was a member of the Groupe de Réflexion sur la creation d'un comité d'éthique en STIC à l'INRIA. Pierre-Yves Oudeyer participated in several meetings of the group "Robotique et Apprentissage" of the GdR Robotique of CNRS. Pierre-Yves Oudeyer was expert for the European Commission for review and evaluations of several FP7 projects and FET calls.

# 9.2. Invited talks

(déc. 2008) Complexité, auto-organisation et développement cognitif, groupe Emergence Paris.

(22 oct. 2008) Les défis de la robotique développementale, Journée du groupe "Robotique et Apprentissage" du GdR Robotique, CNRS, France.

(16 oct. 2008) L'auto-organisation dans l'évolution de la parole, Aux Origines du Dialogue Humain: Parole et Musique, Colloque de rentrée du Collège de France, Paris.

(oct. 2008) La robotique développementale et sociale, Journée INRIA ARC 2008.

(22 sept. 2008) Intrinsically motivated exploration and active learning in developmental robotics, From motor to interaction learning in robots, IROS 2008 workshop, Nice, France.

## 9.3. Teaching

Pierre-Yves Oudeyer gave a 23 hours course on Social and Entertainment Robotics to third year engineering students of ENSTA, Paris.

Pierre-Yves Oudeyer gave a 15 hours course on Social Robotics to second year engineering students of Institut de Cognitique, Bordeaux.

#### 9.4. Communication towards the general public

"Des robots dans les pas du bébé : premiers apprentissages", Inédit n. 66, INRIA.

"Un robot très curieux", La Recherche, Novembre 2008.

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- [1] P.-Y. OUDEYER, F. KAPLAN, V. HAFNER. *Intrinsic Motivation Systems for Autonomous Mental Development*, in "IEEE Transactions on Evolutionary Computation", vol. 11, n<sup>o</sup> 1, 2007, p. 265–286.
- [2] P.-Y. OUDEYER, F. KAPLAN. Intelligent adaptive curiosity: a source of self-development, in "Proceedings of the 4th International Workshop on Epigenetic Robotics", L. BERTHOUZE, H. KOZIMA, C. PRINCE, G. SANDINI, G. STOJANOV, G. METTA, C. BALKENIUS (editors), vol. 117, Lund University Cognitive Studies, 2004, p. 127–130.
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- [5] P.-Y. OUDEYER. Phonemic coding might be a result of sensory-motor coupling dynamics, in "Proceedings of the 7th International Conference on the Simulation of Adaptive Behavior", B. HALLAM, D. FLOREANO, J. HALLAM, G. HAYES, J.-A. MEYER (editors), MIT Press, 2002, p. 406-416.
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- [7] P.-Y. OUDEYER. The Self-Organization of Speech Sounds, vol. 233, n<sup>O</sup> 3, Elsevier, 2005.
- [8] P.-Y. OUDEYER. Self-Organization in the Evolution of Speech, in "Journal of Theoretical Biology", 2006.

## **Year Publications**

#### **Articles in International Peer-Reviewed Journal**

- [9] F. KAPLAN, P.-Y. OUDEYER. *Le corps comme variable expérimentale*, in "Revue Philosophique de la France et de l'Étranger", 2008, p. 287-298, http://www.pyoudeyer.com/kaplan-oudeyer-revuephilo.pdf.
- [10] F. KAPLAN, P.-Y. OUDEYER. Stable kernels and fluid body envelopes, in "SICE Journal of Control, Measurement, and System Intgration", to appear, 2008, http://www.pyoudeyer.com/kaplan-oudeyer-sice09. pdf.

#### **International Peer-Reviewed Conference/Proceedings**

- [11] P.-Y. OUDEYER, A. BARANÈS. Developmental active learning with intrinsic motivation, in "IROS 2008 Workshop : From motor to Interaction learning in robots, Nice, France", 2008, http://www.pyoudeyer.com/ OudeyerBaranesIROS08.pdf.
- [12] P.-Y. OUDEYER, A. BARANÈS. Intrinsically motivated exploration as efficient active learning in unknown and unprepared spaces, in "Proceedings of the 8th International Conference on Epigenetic Robotics : Modeling Cognitive Development in Robotic Systems, Brighton, England", Lund University Cognitive Studies, Lund:LUCS, 2008, http://www.pyoudeyer.com/OudeyerBaranesEpirob08.pdf.
- [13] P.-Y. OUDEYER, F. DELAUNAY. Developmental exploration in the cultural evolution of lexical conventions, in "Proceedings of the 8th International Conference on Epigenetic Robotics : Modeling Cognitive Development in Robotic Systems, Brighton, England", Lund University Cognitive Studies, Lund:LUCS, 2008, http://www. pyoudeyer.com/epirob08-OudeyerDelaunay.pdf.
- [14] P.-Y. OUDEYER, F. KAPLAN. *How can we define intrinsic motivation ?*, in "Proceedings of the 8th International Conference on Epigenetic Robotics : Modeling Cognitive Development in Robotic Systems, Brighton, England", Lund University Cognitive Studies, Lund:LUCS, 2008, http://www.pyoudeyer.com/ epirob08OudeyerKaplan.pdf.

#### **Other Publications**

[15] A. BARANÈS. *Développement et evaluations d'algorithmes de curiosité adaptative*, Masters thesis, Université Paris VI, INRIA, 2008.

- [16] P. ROUANET. Interaction gestuelle robot-humain avec un terminal mobile communicant, Masters thesis, Université Bordeaux 1, INRIA, 2008.
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