

# Activity Report 2015

# **Team LARSEN**

# Lifelong Autonomy and Interaction Skills for Robots in a Sensing Environment

Inria teams are typically groups of researchers working on the definition of a common project, and objectives, with the goal to arrive at the creation of a project-team. Such project-teams may include other partners (universities or research institutions).

RESEARCH CENTER
Nancy - Grand Est

THEME Robotics and Smart environments

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# **Team LARSEN**

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- 5.10.3. Planning
- 5.10.4. Robot control
- 5.10.5. Robot interaction (with the environment, humans, other robots)
- 5.10.6. Swarm robotics
- 5.10.7. Learning
- 5.10.8. Cognitive robotics and systems
- 5.11. Smart spaces
- 5.11.1. Human activity analysis and recognition
- 8.2. Machine learning
- 8.5. Robotics

## **Other Research Topics and Application Domains:**

- 2.1. Well being
- 2.5. Handicap and personal assistances
- 2.5.3. Assistance for elderly

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# 2. Overall Objectives

# 2.1. Overall Objectives

The goal of the LARSEN team is to move robots outside of the research laboratories and manufacturing industries: current robots are far from being the fully autonomous, reliable, and interactive robots that could co-exist with us in our society and run for days, weeks, or months. While there is undoubtedly progress to be made on the hardware side, robotics platforms are quickly maturing and we believe the main challenges to achieve our goal are now on the software side. We want our software to be able to run on low-cost mobile robots that are therefore not equipped with high-performance sensors or actuators, so that our techniques can realistically be deployed and evaluated in real settings, such as in service and assistive robotic applications. We envision that these robots will be able to cooperate with each other but also with intelligent spaces or apartments which can also be seen as robots spread in the environments. Like robots, intelligent spaces are equipped with sensors that make them sensitive to human needs. These intelligent spaces can give robots improved skills, with less expensive sensors and actuators enlarging their field of view of human activities, making them able to behave more intelligently, with better awareness of people evolving in their environment. As robots and intelligent spaces.

Among the particular issues we want to address, we aim at designing robots having the ability to:

- handle dynamic environment and unforeseen situations;
- cope with physical damages;
- interact physically and socially with humans;
- collaborate with each other;
- exploit the multitude of sensors measurements from their surrounding;
- enhance their acceptability and usability by end-users without robotics background.

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All these abilities can be summarized by the following two objectives:

- *life-long autonomy*: continuously perform tasks while adapting to sudden or gradual changes in both the environment and the morphology of the robot;
- *natural interaction with robotics systems*: interact with both other robots and humans for long periods of time, taking into account that people and robots learn from each other when they live together.

# 3. Research Program

# 3.1. Lifelong Autonomy

#### 3.1.1. Scientific Context

So far, only a few autonomous robots have been deployed for a long time (weeks, months, or years) outside of factories or laboratories. They are mostly mobile robots that simply "move around" (e.g., vacuum cleaners or museum "guides") and data collecting robots (e.g., boats or underwater "gliders" that collect data about the water of ocean).

A large part of the long-term autonomy community is focused on simultaneous localization and mapping (SLAM), with a recent emphasis on changing and outdoor environments [33], [48]. A more recent theme is life-long learning: during long-term deployment, we cannot hope to equip robots with everything they need to know, therefore some things will have to be learned along the way. Most of the work on this topic leverages machine learning and/or evolutionary algorithms to improve the ability of robots to react to unforeseen changes [33], [43].

## 3.1.2. Main Challenges

The first major challenge is to endow robots with a stable situation awareness in open and dynamic environments. This covers both the state estimation of the robot itself as well as the perception/representation of the environment. Both problems have been claimed to be solved but it is only the case for static environments [42].

In the LARSEN team, we aim at deployment in environments shared with humans which directly translates into dynamic objects that degrade both the mapping and localization, especially in cluttered spaces. Moreover, when robots stay longer in the environment than for the acquisition of a snapshot map, they have to face structural changes, such as the displacement of a piece of furniture or the opening or closing of a door. The current approach is to simply update an implicitly static map with all observations with no attempt at distinguishing the suitable changes. For localization in not-too-cluttered or not-too-empty environments, this is generally sufficient as a significant fraction of the environment should remain stable. But for life-long autonomy, and in particular navigation, the quality of the map, and especially the knowledge of the stable parts, is primordial.

A second major obstacle to move robots outside of labs and factories is their fragility: current robots often break in a few hours, if not a few minutes. This fragility mainly stems from the overall complexity of robotics systems, which involve many actuators, many sensors, and complex decisions, and from the diversity of situations that robots can encounter. Low-cost robots exacerbate this issue because they can be broken in many ways (high-quality material is expensive), because they have low self-sensing abilities (sensors are expensive and increase the overall complexity), and because they are typically targeted towards non-controlled environments (e.g., houses, by opposition to factories, in which robots are protected from most unexpected events). More generally, this fragility is a symptom of the lack of adaptive abilities in current robots.

#### 3.1.3. Angle of Attack

To solve the state estimation problem, our approach is to combine classical estimation filters (Extended Kalman Filters, Unscented Kalman Filters, or particle filters) with a Bayesian reasoning model in order to internally simulate various configurations of the robot in its environment. This should allow for adaptive estimation that can be used as one aspect of long-term adaptation. To handle dynamic and structural changes in an environment, we aim at assessing, for each piece of observation, whether it is static or not.

We also plan to address active sensing to improve the situation awareness of robots. Literally, active sensing is the fact for an interacting agent – equipped with sensors and effectors – to act so as to control what it senses from its environment. The objective is typically to acquire information about this environment. A good example of such an agent is a mobile robot operating in an unknown or a partially known dynamic environment in order to acquire information about some studied phenomena. Active sensing has applications to autonomous data collection, environment monitoring, sound sources localisation or robotic exploration missions. A formalism for representing and solving active sensing problems has already been proposed by members of the team [32] and we will aim to use it to formalize decision making problems of improving situation awareness.

Situation awareness of robots can also be tackled by cooperation whether it be between robots or between robots and sensors in the environment (led out intelligent spaces) or between robots and humans. We envision here robots with symbiotic autonomy i.e., robots that are aware of their limitations and proactively ask for help from humans, other robots or sensors. This will be addressed and formalized in the framework of distributed sensing. Distributed sensing may include active sensing, but it differs in the fact that a large number of sensors are spread in the environment. Due to recent advances in the development of sensor networks and the rapid growth of the Internet of Things, it is simple, today, to deploy a distributed sensing system. This is why the combination of environmental sensors and robots is especially appealing for monitoring complex environments, cluttered with obstacles and populated by humans. This is in rupture with classical robotics, in which robots are conceived as self-contained: they are composed of actuators, sensors and computers and are designed to carry out a multitude of tasks in full autonomy: localisation, mapping, navigation, interaction, etc. But, in order to cope with as diverse environments as possible, these classical robots use precise, expensive and specialized sensors such as for example 3D laser range finders. However, the cost of these sensors prohibits their use in large-scale deployments for service or assistance applications. Furthermore, when all sensors are on the robot, they share the same point of view on the environment with all that it entails in terms of perception complexity. Therefore, we propose to complement a cheaper robot with sensors distributed in a target environment, gathering the information flow in a usable representation for robots, controlling active sensors such as robots and mobile sensors (camera mounted on a pan-tilt unit). This is an emerging research direction that shares some of the problematics of multi-robot operation - such as synchronization and collaborative planning or swarm intelligence – and sensor networks – such as calibration. We are therefore collaborating with other teams at Inria that address the issue of communication and interoperability.

To address the fragility problem, the traditional approach is to first diagnose the situation, then use a planning algorithm to create/select a contingency plan. The main challenge here is to take uncertainties into account both in the diagnosis and in the planning, a challenge naturally suited for Bayesian methods [45].

An alternative approach is to skip the diagnosis and let the robot discover by trial and error a behavior that works in spite of the damage, that is, to use a reinforcement learning algorithm [54], [43]. This approach could be especially appropriate for low-cost autonomous robots because diagnostic procedures require expensive proprioceptive sensors, and because the possible faults in a complex, autonomous robot that works in an open and dynamic environments are almost infinite. However, current reinforcement learning algorithms require hundreds of trials/episodes to learn a single, often simplified, task [43], which makes them impossible to use for real robots and more ambitious tasks. We therefore need to design new trial-and-error algorithms that will allow robots to learn with a much smaller number of trials (typically, a dozen). We think the key idea is to guide online learning on the physical robot with dynamic simulations. In particular, we will work on combining the exploration abilities of evolutionary algorithms [35] with the convergence speed of gradient-free, continuous, model-based optimization algorithms, like Bayesian Optimization [47], [49]. In our recent work, we successfully mixed evolutionary search in simulation, physical tests on the robot, and machine learning to allow a robot to recover from physical damages [44], [2]. We will continue in this direction.

Another approach to address fragility is to deploy several robots or a swarm of robots or make robots evolve in an active environment. We will consider several paradigms such as (1) those inspired from collective natural phenomena in which the environment plays an active role for coordinating the activity of a huge number of biological entities such as ants; (2) those based on online learning [41]. We envision to transfer our knowledge

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of such phenomenon to engineer new artificial devices such as an intelligent floor (which is in fact a spatially distributed network in which each node can sense, compute and communicate with contiguous nodes and can interact with moving entities on top of it) in order to assist people and robots (see the principle in [52], [41] [18]).

# **3.2.** Natural Interaction with Robotic Systems

#### 3.2.1. Scientific Context

Interaction with the environment is the primordial requirement for an autonomous robot: the robot must rely on measurements from its onboard sensors and, when available, can benefit from exteroceptive sensors distributed in the environment (e.g., external cameras, motion detectors, beacons) in order to model its surrounding and plan its actions based on its status. In this sense, interaction with the environment also includes interaction between the robot and a sensorized environment (sometimes called "smart", "connected", or "robotized") or interaction between the human and this robotics environment. Taking decisions when multiple sensors are spread in such environments is still an open question. In many applications, this requires the capability of the robot to localize itself while moving, and for the environment to fuse the information from its multiple distributed sensors to track the behaviors of robots and humans, analyzing their actions and predicting their intent.

Predicting the evolution of the environment and of the different agents (robots and humans) that populate it, is of primary importance for taking valuable decision in dynamical environments. However, this is still a challenging problem, especially because we lack robust predictive models of human behavior. Using environmental sensors capable to extract main human social or physical signals (e.g., posture or gaze) is a way to simplify the problem for a robot. Putting together information from different sensors and viewpoints is beneficial for robots understanding complex scenes but often significantly increases the complexity of the data and of the representations that can be formed of the environment. At the same time, we aim at being able to control robots or mobile sensors, which means deciding, at each time instant, what to do. A critical constraint is the uncertainty arising both from the incomplete knowledge of the environment and the other agents (typically humans) that share this environment, and from the intrinsic noise of sensors and actuators.

When working in proximity of or directly with humans, robots must be capable of interacting safely with them, which calls upon a mixture of physical and social skills. In particular, robots working outside labs must exhibit the necessary social skills that allow them to interact with people that are not robotics experts. People operating industrial robots are usually specialized operators that receive a proper training for programming and operating the machines [31]. In contrast, the potential end-users of robots for service or personal assistance are usually not familiar with new technologies and robots [46]. To introduce robots in these contexts, the robot must be accepted as a reliable, trustworthy and efficient partner; it must be able to be used by people that are not skilled robotics experts [58], therefore be endowed with the necessary social skills; it must be capable to interact physically with humans, a skill that calls upon its online learning, control and adaptation skills. Despite the growing interest of the robotics community for physical Human-Robot Interaction (HRI) [34], social and collaborative HRI [56], [51], there are few examples in the literature about incorporating human signals in the control of movement and interaction forces. There are also very few examples of whole-body control of robot movement that takes into account human feedback [39]. In psychology, the literature analyzing the social and cognitive aspects of interaction is notable [36], [56]. Sadly, as discussed by [53], most HRI studies focus on verbal communication, and there are only few studies about dyadic interaction with physical contacts with robots. On the contrary, applications such as assistance robotics require a deeper knowledge of the intertwined exchange of social and physical signals to provide suitable robot controllers.

#### 3.2.2. Main Challenges

We are here interested in building the bricks for a situated Human-Robot Interaction (HRI) addressing both the physical and social dimension of the close interaction, and the cognitive aspects related to the analysis and interpretation of human movement and activity.

The combination of physical and social signals into the robot control is a crucial investigation for assistance robots [55] and robotic co-workers [51]. A major obstacle is the control of physical interaction (precisely, the control of contact forces) between the robot and the human, while both partners are moving. In mobile robots, this problem is usually addressed by planning the robot movement taking into account the human as an obstacle or as a target, then delegating the execution of this "high-level" motion to whole-body controllers, where a mixture of weighted tasks is used to account for the robot balance, constraints and desired end-effectors trajectories [37].

The first challenge is to make these controllers easier to deploy in real robotics systems, as currently they require a lot of tuning and can become very complex to handle the interaction with unknown dynamical systems such as humans. Here, the key is to combine machine learning techniques with such controllers.

The second challenge is to make the robot react and adapt online to the human feedback, exploiting the whole set of measurable verbal and non-verbal signals that humans naturally produce during a physical or social interaction. Technically, this means finding the optimal policy that adapts the robot controllers online, taking into account feedback from the human. Here, we need to carefully identify the significant feedback signals or some metrics of human feedback. In real-world conditions (i.e., outside the research laboratory environment) the set of signals is technologically limited by the robot's and environmental sensors and the onboard processing capabilities.

The third challenge is for a robot to be able to identify and track people on board. The motivation is to be able to estimate online either the position, the posture, or even moods and intentions of persons surrounding the robot. The main challenge is to be able to do that online, in real-time and in cluttered environments.

#### 3.2.3. Angle of Attack

Our key idea is to exploit the physical and social signals produced by the human during the interaction with the robot and the environment in controlled conditions, to learn simple models of human behavior. Consequently, use these models to optimize the robot movements and actions. In a first phase, we will exploit the human physical signals (e.g., posture and force measurements) to identify the elementary posture tasks during balance and physical interaction. The identified model will be used to optimize the robot whole-body control, as a prior knowledge that is used to improve both the robot balance and the control of the interaction forces. Technically, we will combine weighted and prioritized controllers with stochastic optimization techniques. To adapt online the control of physical interaction and make it possible with human partners that are not robotics experts, we will exploit verbal and non-verbal signals (e.g., gaze, touch, prosody). The idea here is to estimate online from these signals the human intent along with some inter-individual factors that the robot can exploit to adapt its behavior, maximizing the engagement and acceptability during the interaction.

Another promising approach already investigated in LARSEN team is the capability for a robot and/or an intelligent space to localize humans in its surrounding environment and to understand their activities. This is an important issue to handle both for safe and efficient human-robot interaction.

Simultaneous Tracking and Activity Recognition (STAR) [57] is an approch we want to develop. The activity of a person is highly correlated with its position and this approach aims at combining tracking and activity recognition to benefit one from another. By tracking the individual, the system may help infer its possible activity, while by estimating the activity of the individual, the system may have a better prediction of its possible future positions (which can be very effective in case of occlusion). This direction has been tested with simulator and particle filters [40] and one promising direction would be to couple STAR with decision making formalisms like partially observable Markov decision processes, POMDPs). This would allow to formalize problems such as deciding which action to take given an estimate of the human location and activity. This could also formalize other problems linked to the active sensing direction of the team: how the robotic system might choose its actions in order to have a better estimate of the human location and activity (for instance by moving in the environment or by changing the orientation of its cameras)?

Another issue we want to address is robotic human body pose estimation. Human body pose estimation consists of tracking body parts by analyzing a sequence of input images from single or multiple cameras.

Human posture analysis is of high value for human robot interaction or activity recognition. However, even if the arrival of new sensors like RGB-D cameras has simplified the problem, it still poses a great challenge, especially if we want to do it online, on a robot and in realistic world conditions (cluttered environment). This is even worse for a robot to bring together different capabilities both at the perception and navigation level [38]. This will be tackled through different techniques going from Bayesian state estimation (particle filtering), learning, active and distributed sensing.

# 4. Application Domains

# 4.1. Personal Assistance

During the last fifty years, the many progresses of medicine as well as the improvement of the quality of life have resulted in a longer life expectancy in the industrial societies. The increase of the number of elderly people is a matter of public health because although elderly people can age in good health, old age also causes embrittlement in particular on the physical plan which can result in a loss of autonomy. That will force to re-think the current model regarding the care of elderly people. <sup>1</sup> Capacity limits in specialized institutes, along with the preference of elderly people to stay at home as long as possible, explain a growing need for specific services at home.

Ambient intelligence technologies and robotics could participate to this societal challenge. The spectrum of possible actions in the field of elderly assistance is very large. We will focus on activity monitoring services, mobility or daily activity aids, medical rehabilitation, and social interactions. This will be based on the experimental infrastructure we have build in Nancy (Smart apartment) as well as the deep collaboration we have with OHS.<sup>2</sup>

# 4.2. Civil Robotics

Many applications for robotics technology exist within the services provided by national and local government. Typical applications include civil infrastructure services <sup>3</sup> such as: urban maintenance and cleaning; civil security services; emergency services involved in disaster management including search and rescue; environmental services such as surveillance of rivers, air quality, and pollution. These tasks may be carried out by a wide variety of robot and operating modality ranging from single robots or small fleets of homogeneous or heterogeneous robots. Often robot teams will need to cooperate to span a large workspace, for example in urban rubbish collection, and operate in potentially hostile environments, for example in disaster management. These systems are also likely to have extensive interaction with people and their environments.

The skills required for civil robots match those developed in the LARSEN project: operating for a long time in potentially hostile environment, potentially with small fleets of robots, and potentially in interaction with people.

# 5. Highlights of the Year

# 5.1. Highlights of the Year

- Jean-Baptiste Mouret joined the team (CR1, HDR [8], on secondment from Pierre and Marie Curie University for 5 years);
- The ERC project ResiBots (PI: Jean-Baptiste Mouret) started on the 1st of May, 2015;
- The preliminary work on which the ERC project ResiBots is based made it to the cover of Nature (28th of May, 2015), see figure 1. This work was covered by all the major media outlets and the associated videos total more than 400,000 views on YouTube.

<sup>&</sup>lt;sup>1</sup>See the Robotics 2020 Multi-Annual Roadmap [50], section 2.7.

<sup>&</sup>lt;sup>2</sup>OHS (Office d'Hygiène Sociale) is an association managing several rehabilitation or retirement home structures.

<sup>&</sup>lt;sup>3</sup>See the Robotics 2020 Multi-Annual Roadmap [50], section 2.5.



Figure 1. Cover the Nature issue of the 28th of May, 2015, which features Larsen's work on trial-and-error learning for damage recovery (ResiBots project).

# 6. New Software and Platforms

# 6.1. New Platforms

## 6.1.1. Experimental Room for Robotics

We collaborate on this experimental platform with Olivier Rochel (SED Inria Nancy - Grand Est).

A new room has been installed for the experiments of the ResiBots ERC project and of the Codyco FP7 project (Figure 2). This 100 m<sup>2</sup> room contains a  $5.5 \times 6$  m experimental "arena" made with aluminium trusses.

It is equipped with:

- a 6D motion capture system (Optitrack), with 8 gibagit cameras (Prime 13);
- 4 high-power, studio lights;
- 3 mobile 19" racks (on wheels), which host the power supplies and the computers to control the robots;
- a 6-legged robot, used by the ResiBots project;
- an omnidirectional wheeled robot (Kuka Youbot), used by the ResiBots project;
- a hybrid, wheel-legged robot, used by the ResiBots project (loan by the Pierre and Marie Curie University);
- a Kinova robotic arm, used by the Codyco project.

The trusses support the motion capture system and the lights, and hold all the cables (network, power, etc.). This room will also host the iCub humanoid robot that should be received in March 2016.

# 7. New Results

# 7.1. Lifelong Autonomy

#### 7.1.1. Adaptation / Learning

Participant: Jean-Baptiste Mouret.



Figure 2. Overview of the new experimental room.

We collaborate on this subject with Jeff Clune (University of Wyoming, USA).

#### 7.1.1.1. Adaptation to Unforeseen Damage Conditions

Whereas animals can quickly adapt to injuries, current robots cannot "think outside the box" to find a compensatory behaviour when they are damaged: they are limited to their pre-specified self-sensing abilities and can diagnose only anticipated failure modes, an impracticality for complex robots. A promising approach to reducing robot fragility involves having robots learn appropriate behaviours in response to damage, but current techniques are slow even with small, constrained search spaces. We introduced an intelligent trial-and-error algorithm that allows robots to adapt to damage in less than two minutes in large search spaces without requiring self-diagnosis or pre-specified contingency plans [11]. Before the robot is deployed, it uses a novel technique (based on evolutionary algorithms) to create a detailed map of the space of high-performing behaviours. This map represents the robot's prior knowledge about what behaviours it can perform and their value. When the robot is damaged, it uses this prior knowledge to guide a trial-and-error learning algorithm (based on Bayesian optimization) that conducts intelligent experiments to rapidly discover a behaviour that compensates for the damage. Experiments reveal successful adaptations for a legged robot injured in five different ways, including damaged, broken, and missing legs, and for a robotic arm with joints broken in 14 different ways. This new algorithm will enable more robust, effective, autonomous robots, and may shed light on the principles that animals use to adapt to injury.

This work was the cover of Nature on the 28th of May, 2015 (see the "highlights" section).

#### 7.1.2. Robotics Perception

Participants: François Charpillet, Francis Colas, Abdallah Dib, Van Quan Nguyen.

We collaborate on this subject with Emmanuel Vincent from the Multispeech team (Inria Nancy - Grand Est).

#### 7.1.2.1. Audio Source Localization

We considered, here, the task of audio source localization using a microphone array on a mobile robot. Active localization algorithms have been proposed in the literature that can estimate the 3D position of a source by fusing the measurements taken for different poses of the robot. However, the robot movements are typically fixed or they obey heuristic strategies, such as turning the head and moving towards the source, which may be suboptimal. This work proposes an approach to control the robot movements so as to locate the source as quickly as possible [17]. We represent the belief about the source position by a discrete grid and we introduce a dynamic programming algorithm to find the optimal robot motion minimizing the entropy of the grid. We report initial results in a real environment.

This work is carried on through the PhD Thesis of Van Quan Nguyen under the supervision of Emmanuel Vincent and Francis Colas.

#### 7.1.2.2. State Estimation for Autonomous Surface Vessels

Autonomous Surface Vessels (ASVs) are increasingly proposed as tools to automatize environmental data collection, bathymetric mapping and shoreline monitoring. For many applications it can be assumed that the boat operates on a 2D plane. However, with the involvement of exteroceptive sensors like cameras or laser rangefinders, knowing the 3D pose of the boat becomes critical. We formulated three different algorithms based on 3D extended Kalman filter (EKF) state estimation for ASVs localization [12]. We compared them using field testing results with ground truth measurements, and demonstrated that the best performance is achieved with a model-based solution in combination with a complementary filter for attitude estimation. Furthermore, we presented a parameter identification methodology and showed that it also yielded accurate results when used with inexpensive sensors. Finally, we presented a long-term series (i.e., over a full year) of shoreline monitoring data sets and discussed the need for map maintenance routines based on a variant of the Iterative Closest Point (ICP) algorithm.

7.1.2.3. Geometric Registration

We proposed a review of geometric registration in robotics [16]. Registration algorithms associate sets of data into a common coordinate system. They have been used extensively in object reconstruction, inspection, medical application, and localization of mobile robotics. We focus on mobile robotics applications in which point clouds are to be registered. While the underlying principle of those algorithms is simple, many variations have been proposed for many different applications. In this work, we gave a historical perspective of the registration problem and showed that the plethora of solutions can be organized and differentiated according to a few elements. Accordingly, we presented a formalization of geometric registration and cast algorithms proposed in the literature into this framework. Finally, we reviewed a few applications of this framework in mobile robotics that cover different kinds of platforms, environments, and tasks. These examples allowed us to study the specific requirements of each use case and the necessary configuration choices leading to the registration implementation. Ultimately, the objective of this work is to provide guidelines for the choice of geometric registration configuration.

#### 7.1.2.4. Robust Dense Visual Odometry for RGB-D Cameras in a Dynamic Environment

Visual odometry is a fundamental challenge in robotics and computer vision. The aim of our work is to estimate RGB-D camera motion (onboard a mobile robot) from RGB-D images in a dynamic scene with people moving in the scene. Most of the existing methods have a poor localization performance in such case, which makes them inapplicable in real world conditions. This year, we have proposed a new dense visual odometry method [27] that uses random sampling consensus (RANSAC) to cope with dynamic scenes. We show the efficiency and robustness of the proposed method on a large set of experiments in challenging situations and from publicly available benchmark datasets. Additionally, we compare our approach to another state-of-art method based on M-estimator that is used to deal with dynamic scenes. Our method gives similar results on benchmark sequences and better results on our own dataset.

# 7.1.3. Distributed Sensing and Acting

Participants: Mihai Andries, Amine Boumaza, François Charpillet, Iñaki Fernández Pérez, Nassim Kaldé.

#### We collaborate on this subject with Olivier Simonin from the Chroma team (Inria Grenoble - Rhône Alpes).

#### 7.1.3.1. Localisation of Humans, Objects and Robots Interacting on Load-Sensing Floors

The use of floor sensors in ambient intelligence contexts began in the late 1990's. We designed such a sensing floor in Nancy in collaboration with Hikob company (http://www.hikob.com/) and Inria SED (*service d'expérimentation et de développement*). This is a load-sensing floor which is composed of square tiles, each equipped with two ARM processors (Cortex m3 and a8), 4 load cells, and a wired connection to the four neighboring cells. Ninety tiles cover the floor of our intelligent apartment experimental platform. This load-sensing floor includes as well a LED lighting system which sits flush with the floor surface. This provides people with a new way to interact with their environment at home. This year, we have focused on localisation, tracking and recognition of humans, objects and robots interacting on load-sensing floors [9]. Inspired by computer vision, the proposed technique processes the floor pressure-image by segmenting the blobs containing objects, tracking them, and recognizing their contents through a mix of inference and combinatorial search. The result lists the probabilities of assignments of known objects to observed blobs. The concept was successfully evaluated in daily life activity scenarii, involving multi-object tracking and recognition on low resolution sensors, crossing of user trajectories, and weight ambiguity.

#### 7.1.3.2. Online Distributed Learning for a Swarm of Robots

We propose a novel innovation marking method [22] for neuro-evolution of augmenting topologies in embodied evolutionary robotics. This method does not rely on a centralized clock, which makes it well suited for the decentralized nature of embodied evolution where no central evolutionary process governs the adaptation of a team of robots exchanging messages locally. This method is inspired from event dating algorithms, based on logical clocks, that are used in distributed systems, where clock synchronization is not possible. We compare our method to odNEAT, an algorithm in which agents use local time clocks as innovation numbers, on two multi-robot learning tasks: navigation and item collection. Our experiments showed that the proposed method performs as well as odNEAT, with the added benefit that it does not rely on synchronization of clocks and is not affected by time drifts.

The effect of selection pressure on evolution in centralized evolutionary algorithms (EA's) is relatively well understood. Selection pressure pushes evolution toward better performing individuals. However, distributed EA's in an Evolutionary Robotics (ER) context differ in that the population is distributed across the agents, and a global vision of all the individuals is not available. In this work, we analyze the influence of selection pressure in such a distributed context. We propose a version of mEDEA [22] that adds a selection pressure, and evaluate its effect on two multi-robot tasks: navigation and obstacle avoidance, and collective foraging. Experiments show that even small intensities of selection pressure lead to good performances, and that performance increases with selection pressure. This is opposed to the lower selection pressure that is usually preferred in centralized approaches to avoid stagnating in local optima.

#### 7.1.3.3. Online Distributed Exploration of an Unknown Environment by a Swarm of Robots

This year, we have proposed a new taboo-list approach [18] for multi-robot exploration of unknown structured environments, in which robots are implicitly guided in their navigation on a globally shared map. Robots have a local view of their environment, inside which they navigate in a asynchronous manner. When the exploration is complete, robots gather at a rendezvous point. The novelty consists in using a distributed exploration algorithm which is not guided by frontiers to perform this task. Using the Brick and Mortar Improved ant-algorithm as a base, we add robot-perspective vision, variable vision range, and an optimization which prevents agents from going to the rendezvous point before exploration is complete. The algorithm was evaluated in simulation on a set of standard maps.

Another work [14] carried out within the PhD of Nassim Kaldé concerns exploration in populated environments. The difficulty here is that pedestrian flows can severely impact performances. However, humans have adaptive skills for taking advantage of these flows while moving. Therefore, in order to exploit these human abilities, we propose a novel exploration strategy that explicitly allows for human-robot interactions. Our model for exploration in populated environments combines the classical frontier-based strategy with our interactive approach. We implement interactions where robots can locally choose a human guide to follow and define a parametric heuristic to balance interaction and frontier assignments. Finally, we evaluate to which extent human presence impacts our exploration model in terms of coverage ratio, travelled distance and elapsed time to completion.

# 7.2. Natural Interaction with Robotics Systems

## 7.2.1. Human Characterization

Participants: François Charpillet, Abdallah Dib, Xuan Son Nguyen, Vincent Thomas.

We collaborate on this subject with Olivier Buffet and Alain Dutech from Inria Nancy - Grand Est, Arsène Fansi Tchango and Fabien Flacher from Thales ThereSIS, and Alain Filbois from SED Inria Nancy - Grand Est.

#### 7.2.1.1. Multi-Camera Tracking in Partially Observable Environment

In collaboration with Thales ThereSIS - SE&SIM Team (Synthetic Environment & Simulation), we focus on the problem of following the trajectories of several persons with the help of several controllable cameras. This is a difficult problem since the set of cameras cannot simultaneously cover the whole environment, since some persons can be hidden by obstacles or by other persons, and since the behavior of each person is governed by internal variables which can only be inferred (such as his motivation or his hunger).

The approach we are working on is based on (1) the HMM (Hidden Markov Models) formalism to represent the state of the system (the persons and their internal states), (2) a simulator provided and developed by Thales ThereSIS, and (3) particle filtering approaches based on this simulator. Since activity and location depend on each other, we adopt a Simultaneous Tracking and Activity Recognition approach.

After having shown that it was possible to use a complex behavioral simulator to infer the behavior of complex individuals (motivation, possession, ...) even in case of long periods of occlusions [40], we investigated how to propose a factored particle filter (with one distribution per target) for efficiently tracking multiple targets simultaneously. To that end, we use a Joint Probabilistic Data Association Filter with a particular model of dynamics that largely decouples the evolution of several targets, and turns out to be very natural to apply. We proposed to use a small number of "representatives" of each target to determine and consider only effective interactions among targets.

This work has been published in Arsène Fansi Tchango's PhD thesis which has been defended in December [7].

#### 7.2.1.2. Human Posture Recognition

Human pose estimation in realistic world conditions raises multiple challenges such as foreground extraction, background update and occlusion by scene objects. Most of existing approaches were demonstrated in controlled environments. In this work, we propose a framework to improve the performance of existing tracking methods to cope with these problems. To this end, a robust and scalable framework is provided composed of three main stages. In the first one, a probabilistic occupancy grid updated with a Hidden Markov Model used to maintain an up-to-date background and to extract moving persons. The second stage uses component labelling to identify and track persons in the scene. The last stage uses a hierarchical particle filter to estimate the body pose for each moving person. Occlusions are handled by querying the occupancy grid to identify hidden body parts so that they can be discarded from the pose estimation process. We provide a parallel implementation that runs on CPU and GPU at 4 frames per second. We also validate the approach on our own dataset that consists of synchronized motion capture with a single RGB-D camera data of a person performing actions in challenging situations with severe occlusions generated by scene objects. We make this dataset available online (http://www0.cs.ucl.ac.uk/staff/M.Firman/RGBDdatasets/).

#### 7.2.2. Social Robotics

Participants: Amine Boumaza, Serena Ivaldi.

We collaborate on this subject with Yann Boniface from Loria, Alain Dutech from Inria Nancy - Grand Est and Nicolas Rougier from the Mnemosyne team (Inria Bordeaux - Sud-Ouest).

#### 7.2.2.1. PsyPhINe: Cogito Ergo Es

PsyPhINe is an interdisciplinary and exploratory project (see 9.1.2) between philosophers, psychologists and computer scientists. The goal of the project is related to cognition and behavior. Cognition is a set of processes that are difficult to unite in a general definition. The project aims to explore the idea of assignments of intelligence or intentionality, assuming that our intersubjectivity and our natural tendency to anthropomorphize play a central role: we project onto others parts of our own cognition. To test these hypotheses, our aim is to design a "non-verbal" Turing Test, which satisfies the definitions of our various fields (psychology, philosophy, neuroscience and computer science), using a robotic prototype. Some of the questions that we aim to answer are: is it possible to give the illusion of cognition and/or intelligence through such a technical device? How elaborate must be the control algorithms or "behaviors" of such a device so as to fool test subjects? How many degrees of freedom must it have?

Preliminary experiments with human subjects conducted this past year on a simple device helped to design an experimental protocol and test simple hypotheses which set the ground for the full fledged non verbal Turing Test. This project was funded under a PEPS Mirabelle grant (see 9.1.2) which helped build a robotic device with many degrees of freedom to perform further experiments. We also organized an inter-disciplinary workshop gathering top researchers from philosophy, anthropology, psychology and computer science to discuss and exchange on our methodology (see 10.1.1.1).

#### 7.2.2.2. Multimodal Object Learning During Human-Robot Interaction

Robots working in evolving human environments need the ability to continuously learn to recognize new objects. Ideally, they should act as humans do, by observing their environment and interacting with objects, without specific supervision. However, if object recognition simply relies on visual input, then it may fail during human-robot interaction, because of the superposition of human and body parts. A multimodal approach was then proposed in [15], where visual input from cameras was combined with the robot proprioceptive information, in order to classify objects, robot, and human body parts. We proposed a developmental learning approach that enables a robot to progressively learn appearances of objects in a social environment: first only through observation, then through active object manipulation. We focused on incremental, continuous, and unsupervised learning that does not require prior knowledge about the environment or the robot. In the first phase of the proposed method, we analyse the visual space and detect proto-objects as units of attention that are learned and recognized as possible physical entities. The appearance of each entity is represented as a multi-view model based on complementary visual features. In the second phase, entities are classified into three categories: parts of the body of the robot, parts of a human partner, and manipulable objects. The categorization approach is based on mutual information between the visual and proprioceptive data, and on motion behaviour of entities. The ability to categorize entities is then used during interactive object exploration to improve the previously acquired objects models. The proposed system was implemented and evaluated with an iCub and a Meka robot learning 20 objects. The system was able to recognize objects with 88.5% success rate and create coherent representation models that are further improved by learning during human-robot interaction.

#### 7.2.2.3. Robot Functional and Social Acceptance

To investigate the functional and social acceptance of a humanoid robot, we carried out an experimental study with 56 adult participants and the iCub robot. Trust in the robot has been considered as a main indicator of acceptance in decision-making tasks characterized by perceptual uncertainty (e.g., evaluating the weight of two objects) and socio-cognitive uncertainty (e.g., evaluating which is the most suitable item in a specific context), and measured by the participants' conformation to the iCub's answers to specific questions. In particular, we were interested in understanding whether specific (i) user-related features (i.e., desire for control), (ii) robot-related features (i.e., attitude towards social influence of robots), and (iii) context-related features (i.e., collaborative vs. competitive scenario), may influence their trust towards the iCub robot. We found that participants conformed more to the iCub's answers when their decisions were about functional issues than when they were about social issues. Moreover, the few participants conforming to the iCub's answers for social issues also conformed less for functional issues. Trust in the robot's functional savvy does not thus seem to be a pre-requisite for trust in its social savvy. Finally, desire for control, attitude towards social influence of robots

and type of interaction scenario did not influence the trust in iCub. Results are also discussed with relation to methodology of HRI research in a currently submitted paper (http://arxiv.org/abs/1510.03678 [cs.RO]). This work follows the research on engagement with social robots that was previously published [10].

#### 7.2.2.4. Relation Between Extroversion and Negative Attitude Towards Robot

Estimating the engagement is critical for human - robot interaction. Engagement measures typically rely on the dynamics of the social signals exchanged by the partners, especially speech and gaze. However, the dynamics of these signals is likely to be influenced by individual and social factors, such as personality traits, as it is well documented that they critically influence how two humans interact with each other. We assess the influence of two factors, namely extroversion and negative attitude toward robots, on speech and gaze during a cooperative task, where a human must physically manipulate a robot to assemble an object [23]. We evaluate if the score of extroversion and negative attitude towards robots co-variate with the duration and frequency of gaze and speech cues. The experiments were carried out with the humanoid robot iCub and 56 adult participants. We found that the more people are extrovert, the more and longer they tend to talk with the robot; and the more they will look at the robot hands where the assembly and the contacts occur. Our results confirm and provide evidence that the engagement models classically used in human-robot interaction should take into account attitudes and personality traits.

# 8. Bilateral Contracts and Grants with Industry

# 8.1. Bilateral Contracts with Industry

#### 8.1.1. Emiota

Participant: Jean-Baptiste Mouret.

- Company: Emiota (http://www.wearbelty.com/ / http://www.emiota.fr/)
- Duration: 03/2015 12/2015
- Abstract: Emiota is a startup that works on a "smart" belt: a motorized and sensorized belt that both senses bio-medical data and adapts its length to the activity of its holder. For instance, the belt could tighten if it detects that its holder is getting up and relax if he sits down. In this contract, the Larsen team demonstrated how Bayesian optimization and Gaussian processes, two machine learning techniques used in our recent Nature paper [11], can be used to achieve this adaptation.

# 9. Partnerships and Cooperations

# 9.1. Regional Initiatives

## 9.1.1. AME Satelor

**Participants:** François Charpillet, Maxime Rio, Nicolas Beaufort, Xuan Son Nguyen, Thomas Moinel, Mélanie Lelaure, Théo Biasutto-Lervat.

Economic mobilisation agency in Lorraine has launched a new project Satelor providing it with 2.5 million Euros of funding over 3 years, out of an estimated total of 4.7 million. The leader of the project is Pharmagest-Diatelic. Pharmagest, in Nancy, is the French leader in computer systems for pharmacies, with a 43.5 % share of the market, 9,800 clients and more than 700 employees. Recently, the Pharmagest Group expanded its activities into e-health and the development of telemedicine applications. The Satelor project will accompany the partners of the project in developing services for maintaining safely elderly people with loss of autonomy at home or people with a chronic illness. Larsen team will play an important role for bringing some research results such as:

- developing a low cost environmental sensor for monitoring the daily activities of elderly people at home
- developing a low cost sensor for fall detection
- developing a low cost companion robot able to interact with people and monitoring their activities while detecting emergency situations.
- developing a general toolbox for data-fusion: Bayesian approach.

### 9.1.2. PEPS PsyPhINe: Cogito Ergo Es

Participant: Amine Boumaza.

PEPS site Mirabelle (CNRS & University of Lorraine) gathering researchers from the following institutes: MSH Lorraine (USR3261), InterPsy (EA 4432), APEMAC, EPSaM (EA4360), Archives Henri-Poincaré (UMR7117), Inria Bordeaux Sud-Ouest, Loria (UMR7503). Refer to sec. 7.2.2.1 for further information.

## 9.2. National Initiatives

#### 9.2.1. PIA LAR Living Assistant Robot

Participants: François Charpillet, Abdallah Dib.

Partners : Crédit Agricole, Diatelic, Robosoft

LAR project has the objective to designing an assistant robot to improve the autonomy and quality of life for elderly and fragile persons. The project started at the beginning of the year. The role of the Larsen Team is to develop a simultaneous localisation and mapping algorithm using a RGB-D camera. The main issue is to develop an algorithm able to deal with dynamic environment. Another issue is for the robot to be able to behave with acceptable social skills.

## 9.3. European Initiatives

## 9.3.1. FP7 & H2020 Projects

#### 9.3.1.1. RESIBOTS

**Participants:** Jean-Baptiste Mouret, Dorian Goepp, Konstantinos Chatzilygeroudis, Vassilis Vassiliades, Federico Allocati.

Title: Robots with animal-like resilience Program: H2020 Type: ERC Duration: May 2015 - May 2020 Coordinator: Inria Inria contact: Jean-Baptiste Mouret Abstract: Despite over 50 years of research in robotics, most existing robots are far from being as resilient as the simplest animals: they are fragile machines that easily stop functioning in difficult conditions. The goal of this proposal is to radically change this situation by providing the algorithmic foundations for low-cost robots that can autonomously recover from unforeseen damages in a few minutes. The current approach to fault tolerance is inherited from safety-critical systems (e.g., spaceships or nuclear plants). It is inappropriate for low-cost autonomous robots because it relies on diagnostic procedures, which require expensive proprioceptive sensors, and contingency plans, which cannot cover all the possible situations that an autonomous robot can encounter. It is here contended that trial-and-error learning algorithms provide an alternate approach that does not require diagnostic, nor pre-defined contingency plans. In this project, we will develop and study a novel family of such learning algorithms that make it possible for autonomous robots to quickly discover compensatory behaviors. We will thus shed a new light on one of the most fundamental questions of robotics: how can a robot be as adaptive as an animal? The techniques developed in this project will substantially increase the lifespan of robots without increasing their cost and open new research avenues for adaptive machines.

#### 9.3.1.2. CoDyCo

Participants: Serena Ivaldi, Valerio Modugno, Oriane Dermy.

Title: Whole-body Compliant Dynamical Contacts in Cognitive Humanoids

Program: FP7

Instrument: STREP

Objective: Cognitive Systems and Robotics (b)

Duration: March 2013 - February 2017 (4 years)

Coordinator: Francesco Nori (Italian Institute of Technology)

Partners: TU Darmstadt (Germany), Université Pierre et Marie Curie (France), Josef Stefan Institue (Slovenia), University of Birmingham (UK)

Inria contact: Serena Ivaldi

Abstract: The aim of CoDyCo is to advance the current control and cognitive understanding about robust, goal-directed whole-body motion interaction with multiple contacts. CoDyCo will go beyond traditional approaches: (1) proposing methodologies for performing coordinated interaction tasks with complex systems; (2) combining planning and compliance to deal with predictable and unpredictable events and contacts; (3) validating theoretical advances in real-world interaction scenarios. First, CoDyCo will advance the state-of-the-art in the way robots coordinate physical interaction and physical mobility. Traditional industrial applications involve robots with limited mobility. Consequently, interaction (e.g., manipulation) was treated separately from whole-body posture (e.g., balancing), assuming the robot firmly connected to the ground. Foreseen applications involve robots with augmented autonomy and physical mobility. Within this novel context, physical interaction influences stability and balance. To allow robots to surpass barriers between interaction and posture control, CoDyCo will be grounded in principles governing whole-body coordination with contact dynamics. Second, CoDyCo will go beyond traditional approaches in dealing with all perceptual and motor aspects of physical interaction, unpredictability included. Recent developments in compliant actuation and touch sensing allow safe and robust physical interaction from unexpected contact including humans. The next advancement for cognitive robots, however, is the ability not only to cope with unpredictable contact, but also to exploit predictable contact in ways that will assist in goal achievement. Third, the achievement of the project objectives will be validated in real-world scenarios with the iCub humanoid robot engaged in whole-body goal-directed tasks. The evaluations will show the iCub exploiting rigid supportive contacts, learning to compensate for compliant contacts, and utilizing assistive physical interaction.

## 9.3.2. Collaborations in European Programs, except FP7 & H2020

#### 9.3.2.1. PHC MUROTEX

Participant: François Charpillet.

Program: Hubert Curien Partnerships Project acronym: MUROTEX Project title: Multi-agent coordination in robotics exploration and reconnaissance missions Duration: Jan. 2014 – Dec. 2015

Coordinator: O. Simonin (INSA LYON)

Other partners: Jan Faigl at the Czech Technical University in Prague

Abstract: The main objective of the project is to develop a distributed planning framework for efficient task-allocation planning in exploration and reconnaissance missions by a group of mobile robots operating in an unknown environment with considering communication constraints and uncertainty in localization of the individual team members. One main challenge is to decentralize the decision, in order to scaling up with large fleet of robots (existing solutions are centralized or depend on full communication).

# 9.4. International Research Visitors

## 9.4.1. Visits of International Scientists

9.4.1.1. Internships

• Valerio Modugno, PhD student at the Robotics Lab, DIAG, Sapienza (Rome, Italy), visited LARSEN for 9 months (Apr. 2015 – Dec. 2015) to work on learning of task priorities for a robotic arm.

# **10.** Dissemination

# **10.1. Promoting Scientific Activities**

#### 10.1.1. Scientific Events Organisation

10.1.1.1. Member of the Organizing Committees

- Amine Boumaza co-organized "Tentatives, tentations, intentions", the first workshop of the PsyPhINe project (http://www.msh-lorraine.fr/actualites/single-calendar/tentatives-tentationsintentions/2015/12/).
- François Charpillet co-organized with Jan Jaigl and Olivier Simonin the IROS 2015 workshop "Online decision-making in multi-robot coordination" (http://robotics.fel.cvut.cz/demur15/).
- Serena Ivaldi organized the ICRA 2015 Workshop on Force & Tactile sensing. She also co-organized the BMVA Workshop on Force, vision & tactile sensing for robotics manipulation (http://www.ausy. tu-darmstadt.de/Workshops/ICRA2015TactileForce).

## 10.1.2. Scientific Events Selection

10.1.2.1. Chair of Conference Program Committees

- Serena Ivaldi was co-chair of the track "Learning and Adaptive Systems III" at the IEEE International Conference on Robotics and Automation (ICRA) 2015.
- Jean-Baptiste Mouret was chair of the "Generative and Developmental Systems" track at international Genetics and Evolutionary Computation Conference (GECCO) 2015.

10.1.2.2. Member of Conference Program Committees

- Amine Boumaza was PC member of GECCO'2015 (Genetic and Evolutionary Computation Conference), ECAL'2015 (European Conference on Artificial Life), CEC'2015 (Congress on Evolutionary computation), EA'2015 (Artificial Evolution).
- François Charpillet was a PC member of MSDM 2015 (International Workshop on Multiagent Sequential Decision Making Under Uncertainty), DEMUR'15 (International Workshop on Online Decision-Making in Multi-Robot Coordination), ICAART'2015 (International Conference on Agents and Artificial Intelligence), SENSORNETS'2015 (International Conference on Sensor Networks).
- Serena Ivaldi was PC member of RSS 2015 (Robotics: Science and Systems), associate editor of IROS 2015 (IEEE International Conference on Intelligent Robots and Systems), associate editor of ICRA 2015 (IEEE International Conference on Robotics and Automation), associate editor of HRI 2015 (ACM International Conference on Human-Robot Interaction), associate editor of HUMANOIDS 2015 (IEEE/RAS International Conference on Humanoid Robots). She was also a PC member in several workshops at international conferences (ICRA 2015, AIRO 2015, ACII 2015, ENHANCE 2015).
- Jean-Baptiste Mouret was PC member of GECCO'2015 (Genetic and Evolutionary Computation Conference), ECAL'2015 (European Conference on Artificial Life), and EVOstar'2015.

#### 10.1.2.3. Reviewer

- François Charpillet was a reviewer for the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) and the 2016 IEEE International Conference on Robotics and Automation (ICRA).
- Francis Colas was a reviewer for the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), the Fifth Joint IEEE International Conference on Development and Learning and on Epigenetics Robotics (ICDL-EPIROB), and the 2016 IEEE International Conference on Robotics and Automation (ICRA).
- Serena Ivaldi was a reviewer for the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), the 2015 IEEE/RAS International Conference on Robotics and Automation (ICRA), the 2015 ACM Conference on Human-Robot Interaction (HRI), the 2015 IEEE/RAS International Conference on Humanoid Robots (HUMANOIDS).
- Jean-Baptiste Mouret was a reviewer for the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) and the 2016 IEEE International Conference on Robotics and Automation (ICRA).

### 10.1.3. Journal

#### 10.1.3.1. Member of Editorial Boards

- Serena Ivaldi is member of the editorial board of the Springer Journal of Intelligent Service Robotics.
- 10.1.3.2. Reviewer Reviewing activities
  - Amine Boumaza is a Review Editor for Frontiers in AI and Robotics.
  - François Charpillet was a reviewer for Signal Processing: Image Communication.
  - Francis Colas was a reviewer for Autonomous Robots, the Journal of Intelligent and Robotics Systems, and the Journal of Field Robotics.
  - Serena Ivaldi was a Review Editor for Frontiers in Robotics and AI, a guest Editor for the Springer Journal Autonomous Robots, and a reviewer for IEEE Transaction on Robotics.
  - Jean-Baptiste Mouret was a Review Editor for Frontiers in AI and Robotics, a guest Editor for PLOS Computation Biology, and a reviewer for IEEE Transactions on Evolutionary Computation, PLOS One, Evolutionary Computation, and IEEE Transactions on Robotics.

#### 10.1.4. Invited Talks

- François Charpillet was invited to a round table discussion on acceptability of robotics technology, Entretiens Jacques-Cartier, in Lyon, France.
- Serena Ivaldi gave invited talks on "Social and physical interaction between humans and robots" at the University of Plymouth, UK, at the Technical University of Munich, Germany, at the NETT Workshop 2015 Neural Engineering and related fields, Nancy, France.
- Jean-Baptiste Mouret gave invited talks on "Robots that can adapt to damage in minutes" at the EvoEvo workshop (Satellite workshop at ECAL, the European Conference for Artificial Life), York, UK, at the Ifsttar (PhD days), Aix en Provence, France, and at the Institut des Neurosciences de la Timone (PhD Days), Marseille, France.

#### 10.1.5. Leadership Within the Scientific Community

- François Charpillet is member of the scientific committee of Robotics GDR.
- Serena Ivaldi is member of the CIS task force -web presence- for the IEEE Technical Committee on "Cognitive and Developmental Systems".
- Jean-Baptiste Mouret is chair of the "Evo-Devo-Robot" task force of the IEEE Technical Committee on "Cognitive and Developmental Systems".

#### 10.1.6. Research Administration

- Amine Boumaza is a board member of the Évolution Artificielle association.
- François Charpillet is member of the LORIA laboratory board (*conseil de laboratoire*) and is member of the computer science committee of the doctoral school IAEM.

# 10.2. Teaching - Supervision - Juries

#### 10.2.1. Teaching

- Master: Serena Ivaldi, "Analysis of Human Behavior", 15h eq. TD, M2 Sciences de la Cognitive et Applications, Université de Lorraine, France;
- Master: Vincent Thomas, "Agent intelligent et collectifs", 20h eq. TD, M1 Sciences de la Cognition et Applications, Université de Lorraine, France;
- Master: Vincent Thomas, "Game Design", 20h eq. TD, M1 Sciences de la Cognition et Applications, Université de Lorraine, France;
- Master: Vincent Thomas, "Serious Game", 12h eq. TD, M2 Sciences de la Cognition et Applications, Université de Lorraine, France;
- Master: Vincent Thomas, "Apprentissage numérique", 16h eq. TD, M2 Informatique, Université de Lorraine, France.

#### 10.2.2. Supervision

- PhD: Mihai Andries, "Object and Human Tracking, and Robot Control through a Load-Sensing Floor", Université de Lorraine, 15 Dec. 2015, F. Charpillet (advisor), O. Simonin [6].
- PhD: Arsène Fansi Tchango, "*Reconnaissance comportementale et suivi multi-cible dans des environnements partiellement observés*", Université de Lorraine, 04 Dec. 2015, A. Dutech (advisor), V. Thomas, O. Buffet [7].
- PhD in progress: Adrian Bourgaud, "*Multi-sensor Fusion and Active Sensing*", started in Jul. 2015, François Charpillet (advisor).
- PhD in progress: Konstantinos Chatzilygeroudis, "Diagnosis-free Damage Recovery in Robotics with Machine Learning", started in Oct. 2015, Jean-Baptiste Mouret (advisor).
- PhD in progress: Oriane Dermy, "*Learning to control the physical interaction of a humanoid robot with humans*", started in Nov. 2015, François Charpillet (advisor), Serena Ivaldi.

- PhD in progress: Abdallah Dib, "Assistance à la personne en perte d'autonomie : étude de l'apport d'un robot compagnon", started in Mar. 2013, F. Charpillet (advisor).
- PhD in progress: Iñaki Fernández Pérez, "*Apprentissage incrémental évolutionnaire*", started in Oct. 2013, F. Charpillet (advisor), A. Boumaza.
- PhD in progress: Nassim Kaldé, "*Exploration et reconstruction d'un environnement inconnu par une flottille de robots*", started in Oct. 2012, F. Charpillet (advisor), O. Simonin.
- PhD in progress: Van Quan Nguyen, "Mapping of a sound environment by a mobile robot", started in Dec. 2014, E. Vincent (advisor), F. Colas, F. Charpillet.

## 10.2.3. Juries

- Jean-Baptiste Mouret was member of the PhD committee of:
  - Fabien Benureau, Inria Bordeaux, 18th of May, 2015.
- François Charpillet was member of the HDR committee of:
  - Jean-Baptiste Mouret, Université Pierre et Marie Curie, 16th of June, 2015.
- François Charpillet was reviewer of the HDR of:
  - Fabien Michel, Université de Montpellier, 15th of June, 2015.
- François Charpillet was reviewer of the PhD of:
  - Alan Ali, Ecole Centrale de Nantes, 21st September 2015;
  - Youwei Dong, Ecole centrale de Lille, 16th December 2015.
  - François Charpillet was examiner of the PhD of:
    - Dung Tran, Université de Lorraine, 20th November 2015.

## **10.3.** Popularization

- Amine Boumaza coached a team of programmers that participated in the R2T2 (Remote Rescue using Thymio2) Robot challenge organized by EPFL. The challenge brought together 100 children from 5 countries to save a Martian base using a group of robots (https://www.thymio.org/en:thymio-r2t2).
- Serena Ivaldi was portraited in the book "Le cerveau fait-il deux choses à la fois ?" by Fiamma Luzzatti.
- Jean-Baptiste Mouret gave a talk on "Robots that can adapt to damage in minutes" at Café Neu Romance, Prague (28th of November, 2015)
- Vincent Thomas gave a talk and proposed a tutorial on "physics simulation" during "journées ISN-EPI" (15th of Mars, 2015)
- Vincent Thomas made a presentation about planning for students of Lycée Bichat-Lunéville (19th of Mars, 2015)
- Vincent Thomas participated in "journées Village Master" (9th of April, 2015)
- Vincent Thomas participated in the preparation of "Computer Science Exporoute" (conducted by Inria Nancy Grand Est) planned for 2016
- Vincent Thomas created the exposition "jeux ateliers de la pensée" (http://ticri.univ-lorraine.fr/ wicri-lor.fr/index.php/Exposition\_Jeu) in 2013 with master students from cognitive sciences. This exposition is still presented in several *Bibliothèques Universitaires of Université de Lorraine (BU Brabois, BU St Dié)*.

# 11. Bibliography

# Major publications by the team in recent years

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- [5] O. SIMONIN, F. CHARPILLET, E. THIERRY. Revisiting wavefront construction with collective agents: an approach to foraging, in "Swarm Intelligence", June 2014, vol. 8, n<sup>o</sup> 2, pp. 113-138 [DOI: 10.1007/s11721-014-0093-3], https://hal.inria.fr/hal-00974068

## **Publications of the year**

#### **Doctoral Dissertations and Habilitation Theses**

- [6] M. ANDRIES. Object and human tracking, and robot control through a load sensing floor, Université de Lorraine, December 2015, https://hal.inria.fr/tel-01252938
- [7] A. FANSI TCHANGO. *Behavioral Recognition and multi-target tracking in partially observed environments*, Université de Lorraine, December 2015, https://hal.archives-ouvertes.fr/tel-01251204
- [8] J.-B. MOURET. Evolutionary Adaptation in Natural and Artificial Systems, Université Pierre et Marie Curie, June 2015, Habilitation à diriger des recherches, https://hal.inria.fr/tel-01252289

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

- [9] M. ANDRIES, O. SIMONIN, F. CHARPILLET. Localisation of humans, objects and robots interacting on load-sensing floors, in "IEEE Sensors Journal", 2015, vol. PP, n<sup>o</sup> 99, 12 p. [DOI: 10.1109/JSEN.2015.2493122], https://hal.inria.fr/hal-01196042
- [10] S. M. ANZALONE, S. BOUCENNA, S. IVALDI, M. CHETOUANI. Evaluating the Engagement with Social Robots, in "International Journal of Social Robotics", 2015, pp. 1-14 [DOI: 10.1007/s12369-015-0298-7], https://hal.inria.fr/hal-01158293
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#### **Invited Conferences**

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