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Type de demande :	**Allocation doctorale**
Durée de l'allocation (mois) :	*36 mois*
Titre de la demande	Auto-adaptation à l'environnement vs. Optimisation distribuée d'un critère explicite
Résumé (en français)	Dans le cadre de cette proposition de thèse, nous nous intéressons à la conception d'un algorithme distribué qui devra, en ligne, amener une population d'agents robotique à accomplir une tâche donnée. La description de cette tâche est donnée par un expert humain sous la forme d'une fonction objectif, soit au niveau global, soit au niveau local, sous la forme d'une description des effets attendus (ie. faible corrélation avec l'espace de recherche). L'approche envisagée est celle de l'évolution embarquée (embodied evolutionary robotics) qui a déjà fait ses preuves qui se heurtent à des limites lorsqu'il s'agit d'aborder le cas d'environnements inconnus et potentiellement hostiles (ex. peu de source d'énergie, compromis entre survie et poursuite des objectifs). Il s'agit ici d'étudier les mécanismes d'auto-adaptation dans les sociétés d'insectes pour enrichir des algorithmes d'adaptation par évolution artificielle. En particulier, les résultats en éthologie artificielle et sur les projets travaillant sur les sociétés mixtes robots-insectes, seront exploités pour la conception d'algorithmes d'optimisation pouvant être utilisés sur des plateformes robotiques légères (une centaine de robots à bas prix).

Titre du projet de thèse :

Auto-adaptation à l'environnement vs. Optimisation distribuée d'un critère explicite

Sujet :

1. GENERAL ORGANIZATION

This PhD proposal will be hosted in the Machine Learning and Optimization team (AO) at LRI. It will be integrated into the autonomous robotics research conducted in this team by Nicolas Bredèche.

2. SCIENTIFIC CONTEXT

Current Embodied Evolution approaches face limitations regarding the ability to produce complex behaviors: tasks are usually crafted so that the population of robots may survive easily through the first steps, leaving just the user-defined task to be addressed and the required behaviors to be evolved. However, many situations require complex behaviors just to achieve survival, which is in this case leads to a bootstrap problem. Then, maintaining the balance between self-sustainability and achieving assigned objectives can be a challenge due to contradictory motivations. For example, self-sustainability implies, at least to some degree, opportunities to exchange behavioural strategies (for spreading good behaviors) and cautious exploration, while user-defined tasks may implicitly require coverage of large area (meaning fewer opportunity for convergence) and risky solutions. With few exceptions ([Bianco, 2004], and previous work from one of the advisor [Bredeche et al., 2012, in MCMDS]), few works have tried to address embodied evolution for evolving swarm-level behaviors – that is to provide an online, distributed learning algorithm for real time acquisition of behavioral strategies.

The current PhD project proposal differs from previous projects as we consider all the following features at the same time:

- a large swarm of independent robotic units, as opposed to collective robotics project with medium-size population of robots.
- life-long adaptation through online learning (possibly evolutionary learning)
- goal-driven and environment-driven pressures in the context of a swarm

This PhD proposal is concerned a swarm of autonomous units - such as robots - interacting with one another on a local basis (e.g. limited radio communication range due to hardware limitations or environmental constraints). The goal of this project is to design an algorithmic solution to endow such a swarm with two major properties:

- **self-sustainable property** : the ability to survive in unknown environments, implying self-adaptive mechanisms to face unpredicted situations.
- **controllable property** : the ability to punctually interact with a human interlocutor to achieve assigned tasks during the course of running.

3. OBJECTIVES

This PhD proposal raises several challenges and objectives, which are given here along with our proposed working hypothesis:

Challenge 1: Design self-adaptive algorithmic solution targeting self-sustainable behaviors. To achieve self-sustainability, the robot swarm should be able to demonstrate different kind of behaviors depending on the properties of the environment at hand. This may requires very different kind of swarm behavior, both at the local level (individual strategies) and global level (cooperation strategies). From loosely cooperative behaviors to strongly altruistic behaviors, from homogeneous behaviors to division of labor or spatial division into smaller swarms. This raises the question of self-adaptive algorithms, able to cope with unknown situations and unpredicted changes.

> **Hypothesis 1**. The design of online self-adaptive and learning mechanisms can benefit from lessons learned in Evolutionary Computation and Robotics, and structuring the evolutionary fitness landscape may benefit from results in Artificial Ethology.

Challenge 2: Design algorithmic solution that can cope with contradictory objectives wrt. self-preservation. Addressing user-assigned tasks and preserving one's own integrity may come into conflict, in a more or less dramatic fashion. How to cope with multiple objectives of different nature? How to deal with objective priorities? How to perform risk-management to achieve a user-defined task?

> **Hypothesis 2**. A self-sustainable swarm is mandatory before being able to address user-defined task. Therefore, we should address self-adaptive mechanisms as a first step and primary objective of the swarm, along with risk management solutions.

Therefore, the scientific question is the following: is it possible to design a distributed online (evolutionary) learning algorithm for a robot swarm so that it is able to both (a) ensure long-term survivability of the swarm and (b) enable it to address user-defined tasks?

Such algorithmic solution should then enable the swarm of robotic units to learn how to survive without any external help in unknown (dynamic) environment, possibly through cooperative (even altruistic) behaviors, division of labor, specialization and spatial division (into 2+ smaller more or less independant swarms), depending on the context at hand. The challenge is to address an implicit objective (survive in the environment) in an unknown, possibly dynamic, changing and dangerous environment as well as complying with user-defined objectives, possibly conflicting with self-sustainability.

4. METHOD

The method is based on the design of a distributed on-line evolutionary adaptation algorithm. The expected outcome is thus a self-adaptive swarm, capable of learning self-sustainable behaviors. One important challenge is to consider a individual robots with limited communication and computation capabilities, implying light-weight algorithmic solution (i.e. slow micro-controller, low memory).

As a first step, we will consider recent work from the main advisor [Bredeche, 2012], who proposed a crude but functional algorithm based on the literature on Embodied Evolution, which was experimentally tested in a (relatively small) swarm of 20 real e-puck robots. In its current state, this algorithm shows several major limitations with respect to the environment : a swarm may successfully address self-sustainability, but ignore user-defined objectives.

This PhD thesis will explore the benefits of combining environment-driven and goal-driven Embodied Evolution processes. To some extent, this can be stated as a multi-objective optimization problem, where one objective is hidden in the environment (environmental pressure). We plan to follow the approach started earlier in the team with self-adaptive mechanisms and to explore possible mechanisms to automatically choose the level of attention with which to consider user-specified objectives. The goal is to address environmental constraints in the first place, then to address user-defined objectives. Then, we plan to implement on-board distributed monitoring processes to keep track of the swarm state, so that risk management can be explored (e.g. risking the loss of a small number of robots to address a difficult user-assigned task).

Collective behaviors are usually developed along two different research lines. On the one hand, mechanisms for self-organization are developed from known biological systems such as ants, bees or flocking and shoaling species of birds and fish. Such mechanisms are often based on a dynamical systems description. Agents in a group have specific probabilities of responding to the presence or communication of the others. These response functions are mainly non-linear and include feedback regulations. This approach can be considered as top-down because the behaviors of the individuals are derived from a macroscopic mathematical model like a mean-field approximation with differential equations. The issue is to find the algorithm to be implemented in each individual and the relevant parameters values. This is usually a difficult task that has no known straightforward methodology and is mainly based on educated guesses and tinkering.

On the other hand, evolutionary methods allow evolving rather efficient individual algorithms that produce interesting collective behavior. This approach can be considered as bottom-up because populations of individuals are evolved and selected when they produce interesting collective behavior. However, too often the behavioral complexity levels that are reached with such evolutionary methods are lower than the previous bio-inspired models.

The question arises as how to combine the two approaches and to keep the benefits from both i.e. high behavioral complexities with the practical efficiency of evolutionary methods. Clearly the first approach benefits from the fact that biological systems have been selected by evolution over a long time period. On the artificial evolutionary side, there is still an issue on how to evolve complex individuals that are closer to what is observed in biology. In this thesis we will investigate what are the basic behavioral structures that can be included to bootstrap an evolutionary process to allow the emergence of complex behavioral capabilities similar to living systems. Among other, we plan to explore the impact of nonlinear probability response function at the individual level. First, the link between the sensorial/perceptual capabilities of the agents and such nonlinear function should be formalised and encoded and, second, an appropriate evolutionary mechanism should be designed.

Lastly, this thesis will rely strongly on an experimental approach for the validation of the proposed algorithms. A number of monitoring tools were recently developed to produce automated quantitative ethograms [Branson et al. (2009); Dankert et al. (2009); Reiser (2009)]. They combined the application of modern machine-vision techniques and data analysis by machine learning to quantify animal collective behavior in particular in Drosophila to be capable to perform rapid screening of social behaviors for genetic analysis. Such method will be adapted and used in the context of swarm robotics.

5. EXPECTED RESULTS

The expected outcomes are described below. One preliminary remark is that all major results will involve experiments with real robotic hardware (i.e. simulation will be used in the preliminary and extensive experiments, but the ultimate validation process will be done on real hardware).

Outcome 1. to provide a general purpose algorithmic solution for swarm self-adaption to the context at hand, *a priori* unknown to the human engineer.

Outcome 2. to provide an algorithmic solution that is able to address both environment-driven and goal-driven pressures.

Outcome 3. to provide an algorithmic solution that can be deployed on real hardware (swarm of robots). This is mandatory for the success of the thesis and will be considered from the beginning.

Lastly, it should be noted that the scope of this thesis goes beyond Swarm Robotics. The availability of a distributed self-adaptive algorithm may indeed be relevant in many other domains, such as self-adaptive systems in Autonomic Computing, modeling population of non-playable characters in Video Games, opportunistic optimization tool for agent strategies in multi-agent systems modeling and simulation environments. One additional expected outcome of this project, even if not strictly related to this project, will be to explore the opportunity to apply the designed algorithmic solution to such other domains.