Embodied Evolution for Collective Indoor Surveillance and Location

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ABSTRACT

In this work, the canonical distributed embodied evolution algorithm used to solve a collective task in which a team of Micro Aerial Vehicles (MAVs) has to do surveillance in an indoor area. In order to efficiently survey the arena, the MAVs need to locate themselves and keep track of the recent covered areas and to share this information with other robots. This self-localization is performed using an IMU and a camera by means of artificial landmarks that can be sensed using the onboard camera and the position of other MAV in sight. The accuracy in the location of each MAV arises as a dynamic parameter and has been included as part of the problem to solve. Therefore, the collective control system is in charge of organizing the MAVs in order to increase the surveillance efficiency which is also subject to maintain a suitable accuracy for each of the MAVs.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search– *Heuristics methods.*

General Terms

Algorithms, Navigation

Keywords

Embodied Evolution; Indoor Navigation; Collective Tasks

1. INTRODUCTION

Navigation on indoor scenarios is a widely studied topic in autonomous robotics. To navigate with success, the first issue to solve is the proper location of the robot which is a constrain that is frequently disregarded in situated collective robotics. If it is also required to perform an autonomous and decentralized navigation the location must rely on the onboard sensors of the robot, typically, in the case of a MAV, an inertial measurement unit (IMU), a camera, and distance sensors (infrared, ultrasonic, etc)

The suitability of evolutionary algorithms in the design of control systems for teams of autonomous robots that exploit the coordination between them has been widely tested. One particular evolutionary paradigm which is very convenient to design this sort of collective systems when they required decentralization and are constrained to local interactions between robots, is the so-called Embodied Evolution (EE). EE is inspired by natural evolution and therefore the individuals that make up the population are embodied and situated in an environment where they are forced to interact in a local, decentralized and asynchronous fashion. Hence, evolution in EE is open-ended, leading to a paradigm that is intrinsically adaptive and highly suitable for real time learning in distributed dynamic problems, like the one in this paper. EE interest has grown remarkably in the last decade, with several papers dealing successfully with different collective tasks, both in simulation [1] and real robots [2]. To the authors' best knowledge, this work is the first attempt of using EE for coordinating a fleet of MAVs to perform optimal collective navigation where optimizing localization accuracy is fundamental to perform efficiently.

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2. CANONICAL dEE ALGORITHM

The canonical dEE algorithm [3] generalizes the three basic processes of evaluation, mating and replacement. Moreover, in order to make it independent on the environment and specific task, the relevant evolutionary events have been replaced by stochastic variables, which follow specific probability functions.

- **Mating selection**: it has been modeled as an event that is triggered by a uniform probability function that depends on a single parameter, the probability of mating, that is $P_{mating} = \frac{S_{max}}{T_{max}}$, where S_{max} is the maximum window size of the tournament and T_{max} the maximum lifetime.
- **Selection policy**: the probability of being eligible as a candidate for mating ($P_{elegibility}$) is defined through a function that is based on the fitness value
- **Genotypic recombination**: a new intrinsic parameter is defined: the probability of using a local search strategy (P_{ls}), that is, a mutation operator. It is a measure of the exploration and exploitation balance through the ratio between crossover and mutation frequency.
- **Replacement**: the current canonical EE algorithm considers a fixed population size, therefore the replacement process in this case produces both, the removal of one current individual and the creation of a new one, and is modeled here as triggered by a replacement probability ($P_{replacement}$). This probability is defined based on a more intuitive and manageable parameter, which is the life expectancy (T_{exp}): $P_{replacement} = 1/T_{exp}$. T_{exp} is defined for each individual in each time step based on its current fitness, which depends on its genotype and the genotypes of the others.

3. EXPERIMENTAL SETUP

The experimental setup consists in a simulated indoor surveillance task performed by MAVs. In order to reliably define the simulation (IMU and camera location estimation models), a real scenario was build which uses a Parrot ARDrone 2.0 and visual fiducial markers to allow the image based location. In particular, these markers are the AprilTags designed by the MIT. The use of artificial landmarks provides a drift-free location, unlike the IMU, with a satisfactory position estimation accuracy. In order to improve the performance of the navigation and to enrich the collective problem, the same type of tags (AprilTags) were also attached to the body of the MAVS (mobile tags), which incorporates mobile landmarks to the scenario and the possibility of exchanging location accuracy between MAVs. The left image of Figure 1 displays a schematic representation of the task.

The scenario used in simulation was created as a L^2 (square length units) non-toroidal square area with L=768, which contains four fixed tags at one side, and 40 gatherer MAVs. The rest of parameters of the arena are the maximum speed for a MAV (V_{max} = L/50), the default accuracy degradation ($\Delta A = V_{max}/16$), and the ranges of detection for a fixed and mobile (R_{fix} = L/4 and R_{mob} = L/16). The arena is divided in cells that represent navigation units. Each cell has an exploration probability that depends on the accuracy of the MAV that explores it. This probability decreases gradually over time. With all this, the final objective of the surveillance task is for the fleet of MAVs to continuously cover the maximum uncovered area in the shortest time. The individual fitness function of each individual is calculated based on two variables: the exploration performance and the exchanged accuracy (location accuracy provided to the rest of the fleet). Each individual can be analyzed in terms of its sensors and control unit:

- *Sensors*: available 'explorability' (uncovered cells in near and distant neighborhoods), accuracy available (distance and accuracy of the nearest tag) and current exploration level of the MAV (as a function of its location accuracy).
- *Control unit*: discretizes the input space in 8 different input sets and decides between one of the following behaviors:
  - Explore the near neighborhood
  - Explore the distant neighborhood
  - Search a tag (increase accuracy)
  - Move apart from a tag
  - Stay still to share the available accuracy

The canonical algorithm implementation was tested with the parameters shown in Table 1.

4. RESULTS

In Figure , in left side, the global exploration level is represented as the percentage of explored area of the total area, for each time step and for different levels of accuracy degradation, which represent different environmental conditions in the real scenario. In the right side of Figure 2 and in Figure 3, the task division

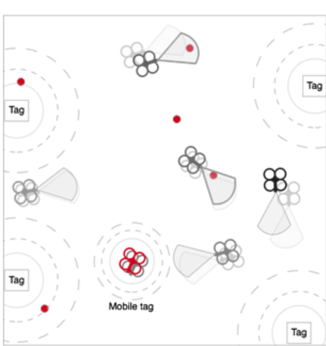

Figure 1: Schematic representation of the scenario

Iterations	10^5
Population size	40
Maximum lifetime (T_{max})	1000
Selection criteria ($P_{elegibility}$)	Higher fitness
Tournament max size (S_{max})	40
Local search probability (P_{ls})	0.99
Chromosome length	8x[1,1]

Table 1. Parameters of the task

performed by the population is displayed by representing the percentage of active behaviors in each time step for the three different degradation levels. It is interesting to note the important variation in the task division for the three different configurations. When the degradation is increased, gathering and sharing location accuracy becomes essential. Contrarily, when there is little or no degradation, exploration becomes a priority.

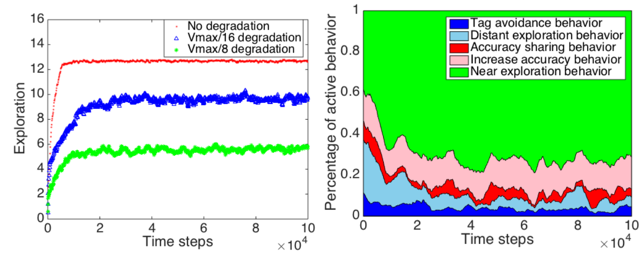

Figure 2: Left: exploration level of the arena over time steps for the different accuracy degradation levels. Right: area chart of the active behaviors in the population for each time step with $\Delta A = V_{max}/16$

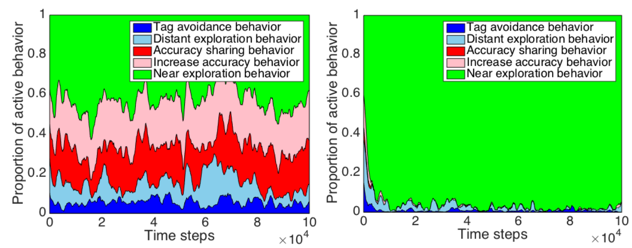

Figure 3: Left: area chart of active behaviors with higher accuracy degradation ($V_{max}/8$). Right: area chart of active behaviors without accuracy degradation.

5. CONCLUSIONS

This work has shown the capability of the canonical Embodied Evolution algorithm to solve, on-line, a collective surveillance task with a fleet of autonomous MAVs. In this case, the optimization problem included the accuracy in the location of the MAVs as a new variable, leading to a coordinated control where the team must cover the scenario, while they are precisely positioned, by sharing their own location information. An emergent specialization has been observed in the final population, with the individuals performing three main sub-tasks.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] Haasdijk, E., Eiben, A.E., Karafotias, G. 2010. On-line evolution of robot controllers by an encapsulated evolution strategy, *Proceedings IEEE CEC2010*, 1-7

[2] Bredeche, N., Montanier, J.M., Liu, W., Winfield, A. 2012. Environment-driven Distributed Evolutionary Adaptation in a Population of Autonomous Robotic Agents, *Mathematical and Comp. Modelling of Dynamical Systems* 18, 1, 101-129

[3] Trueba, P., Prieto, A., Bellas, F. 2013. Distributed embodied evolution for collective tasks: parametric analysis of a canonical algorithm, *Proceedings GECCO2013*, 37-38