Unleashing the Potential of Evolutionary Swarm Robotics in the Real World

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ABSTRACT

We provide a summary of our real-world experiments with a swarm of aquatic surface robots with evolved control. Robotic control was synthesized in simulation, using offline evolutionary robotics techniques, and then successfully transferred to a real swarm. Our study presents one of the first demonstrations of evolved control in a swarm robotics system outside of controlled laboratory conditions. *Original publication: M. Duarte, V. Costa, J. Gomes, T. Rodrigues, F. Silva, S. M. Oliveira, and A. L. Christensen. Evolution of collective behaviors for a real swarm of aquatic surface robots. PLoS ONE, 11(3):e0151834, 2016.*

1. INTRODUCTION

Swarm robotics systems (SRS) are a promising approach to collective robotics, in which large groups of relatively simple and autonomous robots display collectively intelligent behavior [2]. Control in a SRS is decentralized, meaning that each individual robot operates based on local observations and in coordination with neighboring robots. Due to their inherent properties, namely robustness, flexibility and scalability, SRS have an enormous potential in several real-world domains, such as search and rescue, exploration, surveillance, and cleanup [1, 2].

One of the key challenges in SRS is the synthesis of behavioral control. In this respect, evolutionary robotics (ER) techniques have been widely studied as an alternative to manual control design, due to their capacity to automatically synthesize self-organized control based only on a specification of a high-level performance metric [4]. Despite the potential of SRS with evolved control for real-world tasks, previous experiments presented in the literature have been confined to laboratory environments such as enclosed arenas, in which the relevant experimental conditions can be controlled [2]. In this paper, we summarize recent studies that have shown, for the first time, a SRS system with evolved, decentralized control carrying out proof-of-concept tasks in real-world environments (see Fig. 1).

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Figure 1: Ten robots performing a homing task.

2. EVOLUTION OF SWARM BEHAVIORS FOR AQUATIC ROBOTS

In [5], we studied the evolution and transfer of swarm robotic behavior in a real-world maritime task environment. We considered four canonical swarm robotics tasks in this study: (i) *homing*, where the robots had to collectively navigate to a waypoint while avoiding collisions, (ii) *dispersion*, where the robots had to keep a target distance to the nearest neighbor, (iii) *clustering*, where the robots had to find each other and aggregate, and (iv) *monitoring*, where the robots had to continuously cover a given area.

We adopted the following methodology to synthesize controllers for each task, and to systematically evaluate the transfer of the controllers to the real robotic swarm:

Definition of the simulation platform: we used a 2D simulator with simplified physics. The robots' movement properties were modeled based on real-robot measurements.

Configuration of sensors and actuators: the robot controller received as inputs the distance to objects of interest in equal-sized segments around the robot, and outputted the robot's speed and direction. To account for the stochasticity of the environment and facilitate the transferability from simulation to the real robots, we used conservative amounts of noise in the sensors and actuators in simulation.

Definition of the fitness functions: For each task, we specified a fitness function that translated the task objective that needed to be achieved. To evaluate each candidate solution (controller), multiple simulation trials were conducted, varying the number of robots and the initial conditions.

Evolution of robotic control: We used the NEAT evolutionary algorithm to synthesize the neural network controllers for the robots.

Selection of the highest-performing controllers: For each task, we identified the highest-performing controllers, according to their fitness score. We selected three controllers from different evolutionary runs for each task.

Assessment in the real SRS: the real-robot performance of the controllers was compared to their performance in simulation. Each controller was tested in three trials, and key metrics from each task were extracted in order to enable comparison of performance between simulation and reality.

The study was conducted on a SRS composed of ten small (65 cm in length), simple, and inexpensive ($\approx$ 300 eur/unit) aquatic surface robots [3]. Each robot was a differential drive mono-hull boat with a maximum speed of 1.7 m/s. The robots communicated with the nearby neighbors using an ad-hoc Wi-Fi network, and were equipped with GPS and compass. The experiments were conducted in a semi-enclosed aquatic environment with a size of 330 m $\times$ 190 m.

Overall, the results showed that the controllers were able to successfully cross the reality gap, as they displayed similar behaviors and levels of performance in simulation and in the real environment. A number of unexpected factors affected the real-robot experiments, such as temporary motor failures, speed differences, and communication failures, but the swarm behaviors were robust to these variations and they did not significantly affect task performance.

We further conducted a set of experiments to verify key properties of SRS, namely scalability and robustness. Scalability was tested by evaluating the same controller with swarms of different sizes, and robustness was tested by adding or removing robots to the swarm during task execution. Our results showed that the controllers scaled well with the swarm size, and that the swarm was able to adapt to changing and unforeseen conditions while still successfully carrying out the task, demonstrating that the aforementioned key swarm properties are present in our system.

3. RECENT DEVELOPMENTS

Monitoring Large-scale Environments: The study presented in [7] applied the previously synthesized controllers to an environmental monitoring task, where the robots collected water temperature data in a pre-defined area. The results showed how the cooperative movement pattern of the robots enabled them to effectively cover differently shaped areas that were not considered during the evolutionary process. We additionally showed in simulation how the evolved behaviors could scale to groups of up to 50 robots, areas of up to 625 ha, and were robust to frequent faults in the individual robots.

Decomposing Control for Complex Missions: In [6], we applied the *hierarchical control synthesis* approach to solve an intruder detection task, where robots have to navigate to an area of interest, monitor the area, detect and follow intruders that cross the area, periodically return to the base station for recharging. We used a *hybrid* control algorithm, where a top-level manually programmed finite state machine arbitrated the low-level evolved behavior primitives. We demonstrated how hybrid controllers can produce modular and flexible swarm behaviors, and enable the control of swarm robotics systems in complex tasks with realistic constraints.

Behaviorally Heterogeneous Teams: In a recent study [8], we have shown how cooperative coevolutionary algorithms (CCEAs) can be used to produce behaviorally heterogeneous control for teams of aquatic robots. In simulation, we evolved control for a cooperative predator-prey pursuit task, where a team of three predators had to coordinate to capture a prey. We then tested a wide variety of teams in the real robots, most of which transferred without loss of performance. This study is among the first demonstrations of CCEAs applied to teams of real robots.

4. CONCLUSION

The study presented in [5], and the subsequent related studies [6–8], have demonstrated that ER can be successfully applied to evolve control for swarm robotics systems that operate in real-world, uncontrolled conditions. We demonstrated evolved control in a variety of tasks of different complexity, and using different control synthesis approaches. Future work will focus in moving from a proof-of-concept robotic platform to a seaworthy platform that can be applied to real-world missions. We will therefore need to address issues such as integration of control with gathered sensory information, fault detection and fault tolerance, and autonomous recharging.

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