Adaptive navigation in a heterogeneous swarm robotic system

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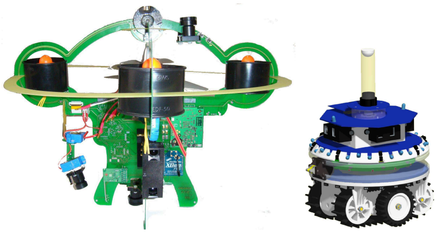
Abstract

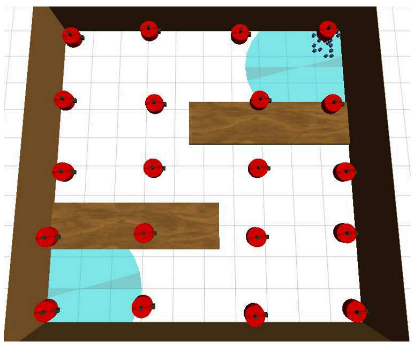
We study a situation where a swarm of wheeled robots, the foot-bots, is deployed in an indoor environment to solve a foraging problem, i.e., they need to go back and forth between a source and a target location. For the navigation between the two locations, they are assisted by a swarm of flying robots that can attach to the ceiling, the eye-bots. The eye-bots are deployed beforehand and form a grid on the ceiling between source and target. From their position on the ceiling they give directional instructions to the foot-bots on the ground. Since the topology of the terrain is different on the ceiling and on the ground, eye-bots cannot derive the instructions to give based on their own sensor feedback (e.g., distance scanner, or infrared communication between eye-bots). Instead, we use an iterative solution whereby eye-bots give instructions to foot-bots and then observe the behavior and feedback of footbots to adapt the instructions they give. Through this adaptive process, the heterogeneous system of eye-bots and foot-bots is able to cooperatively learn paths through the environment. Moreover, it is capable of finding shortest paths and spreading over multiple paths in case of congestion. We describe both a swarm intelligence inspired approach and an approach using reinforcement learning. The setup described here relates to existing work on the use of sensor networks to guide robots or persons through cluttered environments. Moreover, the proposed approach shows how stigmergic reinforcement learning can be applied in swarm robotic systems.

1 The robots



The eye-bot (prototype) and the foot-bot (CAD design), developed in the Swarmanoid project.

2 Problem description

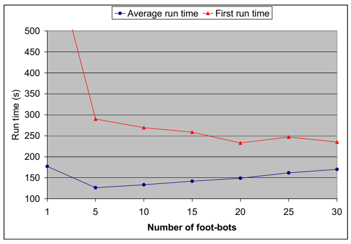


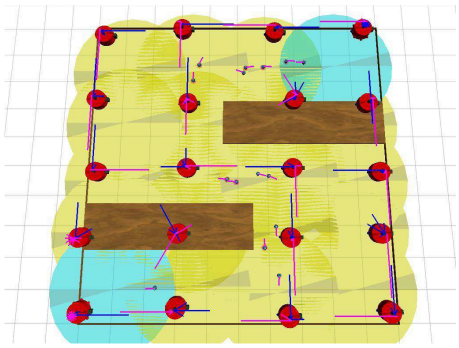
Eye-bots attach to the ceiling and form a grid. Foot-bots are deployed in the source location at the top right of the arena. The target location is at the bottom left. Eye-bots need to guide foot-bots between source and target, but obstacles on the ground cannot be detected by eye-bot sensors.

3 An adaptive solution

- Eye-bots give directions to foot-bots, drawing randomly from two policies (one for the target and one for the source)
- Foot-bots give feedback about their behavior
  - Direction they come from
  - Whether they perform obstacle avoidance
- Eye-bots update their policies based on this feedback

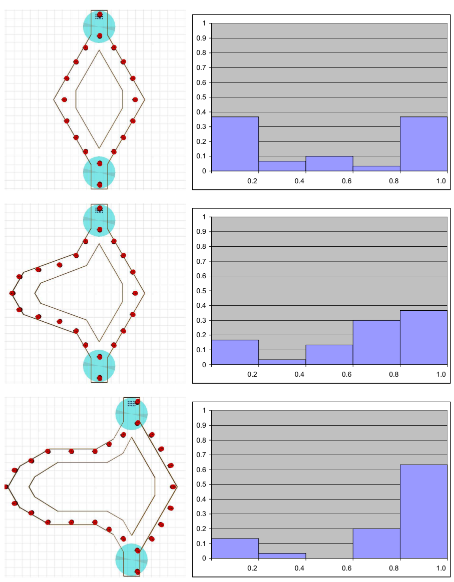
For the scenario above, we run tests with increasing numbers of foot-bots. We report the time needed by the first foot-bot to find the target, and the average time needed by foot-bots to go between source and target. The results show that the system learns a path for foraging. We also show a snapshot of the system after 500 s (lines above eye-bots show policies).





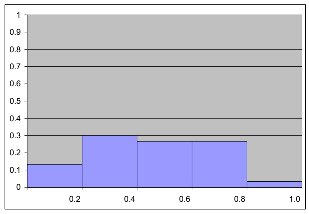
4 Shortest path

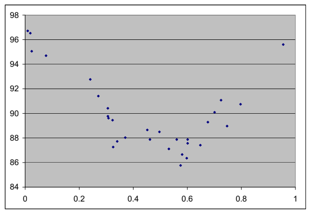
Our approach has similarities with pheromone based foraging of ants. Eye-bots serve as stigmergic communication points for foot-bots. Like ants, our system is able to converge onto a shortest path. We carry out tests with 15 foot-bots in double bridge scenarios, and measure the distribution of foot-bots over the branches (number of foot-bots observed on right branch divided by total number of foot-bots observed on both branches). We show a histogram summarizing the observations over 30 independent runs.



5 Self-organized spreading

Ants automatically spread over multiple paths in case of congestion. Our system has similar behavior, because eye-bots reduce their policy in directions where foot-bots perform obstacle avoidance. For experiments with equal branches using 25 foot-bots, we show the distribution of foot-bots over the branches (top), and the average run time versus the foot-bot distribution (bottom).

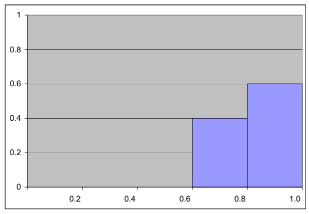




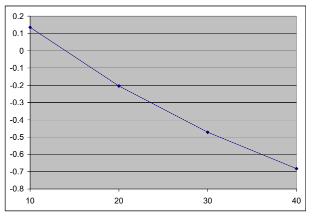
6 Reinforcement learning

We replace feedback about foot-bot behavior by explicit feedback about foot-bot travel times. Eye-bots update their policies using reinforcement learning. The system implements stigmergic reinforcement learning for swarm robotics.

In double bridge experiments, the system always finds the shortest path.



In case of congestion, the system is able to separate opposite flow directions. For experiments with increasing numbers of foot-bots in the setup with equal branch lengths, we measure the distribution over branches separately for foot-bots going towards the target and foot-bots going towards the source. We show that the correlation between the two becomes negative for increasing numbers of foot-bots, which indicates that robots use a different way to go and to come back.



7 References

F. Ducatelle, G.A. Di Caro and L.M. Gambardella. Cooperative Self-Organization in a Heterogeneous Swarm Robotic System. *Technical report IDSIA-01-10*, 2010. Note: submitted to GECCO 2010.

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