Chapter 4.10
The Application of Swarm Intelligence to Collective Robots

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ABSTRACT

This chapter considers the application of swarm intelligence principles to collective robotics. Our aim is to identify the reasons for the growing interest in the intersection of these two areas, and to evaluate the progress that has been made to date. In the course of this chapter, we will discuss the implications of taking a swarm intelligent approach, and review recent research and applications. The area of "swarm robotics" offers considerable promise for practical application, although it is still in its infancy, and many of the tasks that have been achieved are better described as "proof-of-concept" examples, rather than full-blown applications. In the first part of the chapter, we will examine what taking a swarm intelligence approach to robotics implies, and outline its expected benefits. We shall then proceed to review recent swarm robotic applications, before concluding with a case study application of predator-prey robotics that illustrates some of the potential of the approach.

TAKING A SWARM INTELLIGENCE APPROACH TO COLLECTIVE ROBOTICS

What is Swarm Intelligence?

To be able to deliberate over the reasons for taking a swarm intelligence approach to collective robotics, we need to first provide an account of what swarm intelligence is. Swarm intelligence is a comparatively recently articulated notion. The concept was first introduced by Beni and Wang (1989) in their investigations of simulated selforganising agents in the context of cellular robotic systems. A more extensive definition was provided by Bonabeau, Dorigo, and Theraulaz (1999), who suggested the term should be applied to:

any attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insect colonies … and other animal societies.

Agassounon, Martinoli, and Easton (2004) suggest that swarm intelligence takes its inspiration:

from the biological examples provided by social insects … such as ants, termites, bees, and wasps, and by swarming, flocking, herding, and shoaling phenomena in vertebrates.

By contrast, Martinoli (1999) asserts that such bio-inspiration is not necessary, and that the defining characteristic of swarm intelligence should be an emphasis on local control and communication (as opposed to global), claiming that:

swarm intelligence arises from local interactions and is based on local information and communication mechanisms. (Martinoli, 1999)

Nonetheless, an emphasis on local as opposed to global interaction is itself clearly biologically-inspired. Bonabeau and Theraulaz (2000) suggest the term "swarm intelligence" is applicable to the "collective behaviour that emerges from a group of social insects". It would seem then, that the term can be applied to both the emergent collective behaviour of biological swarms or colonies, *and* to algorithms inspired by living systems.

In either case, the notion of swarm intelligence is grounded in an awareness of the sophisticated collective behaviour that can emerge from the combination of many simple individuals, each operating autonomously. Despite their often extensive size—colonies of the African driver ant *Anomma wilverthi* may contain as many as 22 million workers patrolling an area as much as 50,000 square meters in extent (Raignier & van Boven, 1955)—insect societies are able to maintain themselves as a collective, and to accomplish the coordinated action needed to construct nests, to feed and raise their young, and to react to invasion or other interference despite, or perhaps because of, the limited behavioural and representational capabilities of their individual members, and the absence of centralised control mechanisms.

Swarm intelligence algorithms have been shown to be useful for both static problems (for example, application of the ant colony system to the *travelling salesperson problem*—Dorigo & Gambardella, 1997), and dynamic problems, notably load balancing in telecommunication networks (Schoonderwoerd, Holland, Bruten, & Rothkrantz, 1997). In the ant colony system's solution for the travelling salesperson problem, a set of agents, or "ants" search for good solutions and communicate through pheromone-mediated indirect communication. The results show the system to be competitive with other heuristic algorithms such as genetic algorithms, evolutionary programming, and simulated annealing. Interestingly, although the system is biologically inspired, its operation departs from that of real ants through the introduction of faster pheromone decay. In real ants, if a shorter path is presented after a longer path, it is not adopted because the longer path will have been marked by pheromone; whereas in an artificial system, this problem is avoided by introducing pheromone decay (Bonabeau & Theraulaz, 2000). The work of Schoonderwoerd et al. (1997) also relies in the application of an ant colony algorithm, and on the removal of obsolete solutions by applying a mathematical version of pheromone evaporation.

A swarm intelligence approach has then been applied to a number of tasks and practical applications. The notion, abstracted away from biology, depends on decentralised local control of a large number of simple agents. The role of the