Chapter XV
Guiding Self-Organization in Systems of Cooperative Mobile Agents

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ABSTRACT

Drawing inspiration from social interactions in nature, swarm intelligence has presented a promising approach to the design of complex systems consisting of numerous, simple parts, to solve a wide variety of problems. Swarm intelligence systems involve highly parallel computations across space, based heavily on the emergence of global behavior through local interactions of components. This has a disadvantage as the desired behavior of a system becomes hard to predict or design. Here we describe how to provide greater control over swarm intelligence systems, and potentially more useful goal-oriented behavior, by introducing hierarchical controllers in the components. This allows each particle-like controller to extend its reactive behavior in a more goal-oriented style, while keeping the locality of the interactions. We present three systems designed using this approach: a competitive foraging system, a system for the collective transport and distribution of goods, and a self-assembly system capable of creating complex 3D structures. Our results show that it is possible to guide the self-organization process at different levels of the designated task, suggesting that self-organizing behavior may be extensible to support problem solving in various contexts.

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INTRODUCTION

The term *swarm intelligence*, initially introduced by Beni, 1988 in the context of cellular robotics, refers to a collection of techniques inspired in part by the behavior of social insects, such as ants, bees, termites, etc., and of aggregations of animals, such as flocks, herds, schools, and even human groups and economic models (Bonabeau, 1999; Kennedy, 2001). These swarms possess the ability to present remarkably complex and "intelligent" behavior, despite the apparent lack of relative complexity in the individuals that form them. These behaviors can include cooperative synchronized hunting, coordinated raiding, migration, foraging, path finding, bridge construction, allocation of labor, and nest construction. Past discoveries (Deneubourg, 1989) have led investigators to the belief that such behaviors, although in part produced by the genetic and physiological structure of the individuals, are largely caused by the *self-organization* of the systems they form (Aron, 1990; Bonabeau, 1996). In other words, out of the direct or indirect local interactions between the individuals, the collective behavior emerges in a way that may have the appearance of being globally organized, although no centralized control or global communication actually exists. It is precisely this self-organization that artificial swarm intelligence systems try to achieve, by infusing the components, homogeneous or heterogeneous, of a system with simple rules. Swarm intelligence presents a novel and promising paradigm for the design and engineering of complex systems, increasingly found in many fields of engineering and science, where the number of elements and the nature of the interactions among them make it considerably difficult to model or understand the system's behavior by traditional methods.

Several methodological approaches to swarm intelligence have been explored, but they often share a common feature: collections of simple entities (simulated birds, ants, vehicles, etc.) move autonomously through space, controlled by forces or interactions exerted locally upon each other, either directly or through the environment. These local interactions are often governed in a simple manner, via small sets of rules or short equations, and in some cases the sets of reactive agents used are best characterized as *particle systems* where each agent is viewed as a particle. This provides swarming systems with a sets of properties that includes scalability, fault tolerance, and perhaps more importantly, self-organization. Through this latter property, there is no need for a system to be controlled in a hierarchical fashion by one or more central components that determine the required behavior of the system. Instead, collective behavior emerges from the local interactions of all the components, and the global system behaves as a super-organism of loosely connected parts that react "intelligently" to the environment.

In our view, the self-organizing feature of swarm systems represents its main advantage and also its main disadvantage: the resulting global behavior is often hard to predict based solely on the local rules, and in some cases it can be hard to control the system, that is, to obtain a desired behavior by imposing local rules on its components. This not only can require prolonged, trial-and-error style tweaking and fine tuning, but even limits the kinds of problems that can be tackled by these essentially reactive systems.

In our ongoing research in swarm intelligence (Grushin, 2006; Lapizco, 2005; Rodriguez, 2004; Winder, 2004), we have proposed, and shown to be partially successful, an approach to overcome these limitations: the introduction of layered controllers into the previously purely reactive particles or components of a system. The layered controllers allow each particle to extend its reactive behavior in a more goal-oriented style, switching between alternative behaviors in different contexts, while retaining the locality of the interactions and the general simplicity of the system. In this way, by providing a larger, more complex set of behaviors for the particles and finer control over them, the resulting system remains self-organizing, but a

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