Swarm Intelligence: Literature Overview

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1 Swarms

A long time ago, people discovered the variety of the interesting insect or animal behaviors in the nature. A flock of birds sweeps across the sky. A group of ants forages for food. A school of fish swims, turns, flees together, etc.[1]. We call this kind of aggregate motion "swarm behavior." Recently biologists, and computer scientists in the field of "artificial life" have studied how to model biological swarms to understand how such "social animals" interact, achieve goals, and evolve. Moreover, engineers are increasingly interested in this kind of swarm behavior since the resulting "swarm intelligence" can be applied in optimization (e.g. in telecommunicate systems) [2], robotics [3, 4], traffic patterns in transportation systems, and military applications [5].

A high-level view of a swarm suggests that the N agents in the swarm are cooperating to achieve some proposeful behavior and achieve some goal. This apparent "collective intelligence" seems to emerge from what are often large groups of relatively simple agents. The agents use simple local rules to govern their actions and via the interactions of the entire group, the swarm achieves its objectives. A type of "self-organization" emerges from the collection of actions of the group.

Swarm intelligence is the emergent collective intelligence of groups of simple autonomous agents. Here, an autonomous agent is a subsystem that interacts with its environment, which probably consists of other agents, but acts relatively independently from all other agents. The autonomous agent does not follow commands from a leader, or some global plan [6]. For example, for a bird to participate in a flock, it only adjusts its movements to coordinate with the movements of its flock mates, typically its "neighbors" that are close to it in the flock. A bird in a flock simply tries to stay close to its neighbors, but avoid collisions with them. Each bird does not take commands from any leader bird since there is no lead bird. Any bird can fly in the front, center and back of the swarm. Swarm behavior helps birds take advantage of several things including protection from predators (especially for birds in the middle of the flock), and searching for food (essentially each bird is exploiting the eyes of every other bird).

1.1 Biological Basis and Artificial Life

Researchers try to examine how collections of animals, such as flocks, herds and schools, move in a way that appears to be orchestrated. A flock of birds moves like a well-choreographed dance troupe. They veer to the left in unison, then suddenly they may all dart to the right and swoop down toward the ground. How can they coordinate their actions so well? In 1987, Reynolds created a "boid" model, which is a distributed behavioral model, to simulate on a computer the motion of a flock of birds [7]. Each boid is implemented as an independent actor that navigates according to its own perception of the dynamic environment. A boid must observe the following rules. First, the "avoidance rule" says that a boid must move away from boids that are too close, so as to reduce the chance of in-air collisions. Second, the "copy rule" says a boid must fly in the general direction that the flock is moving by averaging the other boids' velocities and directions. Third, the "center rule" says that a boid should minimize exposure to the flock's exterior by moving toward the perceived center of the flock. Flake [6] added a fourth rule, "view," that indicates that a boid should move laterally away from any boid the blocks its view. This boid model seems reasonable if we consider it from another point of view, that of it acting according to attraction and repulsion between neighbors in a flock. The repulsion relationship results in the avoidance of collisions and attraction makes the flock keep shape, i.e., copying movements of neighbors can be seen as a kind of attraction. The center rule plays a role in both attraction and repulsion. The swarm behavior of the simulated flock is the result of the dense interaction of the relatively simple behaviors of the individual boids.

One of the swarm-based robotic implementations of cooperative transport is inspired by cooperative prey retrieval in social insects. A single ant finds a prey item which it cannot move alone. The ant tells this to its nestmate by direct contact or trail laying. Then a group of ants collectively carries the large prey back. Although this scenario seems to be well understood in biology, the mechanisms underlying cooperative transport remain unclear. Roboticists have attempted to model this cooperative transport. For instance, Kube and Zhang [2] introduce a simulation model including stagnation recovery with the method of task modeling. The collective behavior of their system appears to be very similar to that of real ants.

Resnick [8] designed StarLogo – an object-oriented programming language based on Logo, to do a series of microworld simulations. He successfully illustrated different self-organization and decentralization patterns in the slime mold, artificial ants, traffic jams, termites, turtle and frogs and so on.

Terzopooulos et al. [9] developed artificial fishes in a 3D virtual physical world. They emulate the individual fish's appearance, locomotion, and behavior as an autonomous agent situated in its simulated physical domain. The simulated fish can learn how to control internal muscles to locomote hydrodynamically. They also emulated the complex group behaviors in a certain physical domain.

Millonas [10] proposed a spatially extended model of swarms in which organisms move probabilistically between local cells in space, but with weights dependent on local morphgenetic substances, or morphogens. The morphogens are in turn affected by the paths of movements of an organism. The evolution of morphogens and the corresponding flow of the organisms constitutes the collective behavior of the group.

Learning and evolution are the basic features of living creatures. In the field of artificial life, a variety of species adaptation genetic algorithms are proposed. Sims [11] describes a lifelike system for the evolution and co-evolution of virtual creatures. These artificial creatures compete in physically simulated 3D environments to seize a common resource. Only the winners survive and reproduce. Their behavior is limited to physically plausible actions by realistic dynamics, like gravity, friction and collisions. He structures the genotype by the directed graphs of nodes and connections. These genotypes can determine the neural systems for controlling muscle forces and the morphology of these creatures. They simulate co-evolution by adapting the morphology and behavior mutually during the evolution process. They found interesting and diverse strategies and counter-strategies emerge during the simulation with populations of competing creatures.

1.2 Swarm Robots

Swarm robotics is currently one of the most important application areas for swarm intelligence. Swarms provide the possibility of enhanced task performance, high reliability (fault tolerance), low unit complexity and decreased cost over traditional robotic systems. They can accomplish some tasks that would be impossible for a single robot to achieve. Swarm robots can be applied to many fields, such as flexible manufacturing systems, spacecraft, inspection/maintenance, construction, agriculture, and medicine work [12].

Many different swarm models have been proposed. Beni [4] introduced the concept of cellular robotics systems, which consists of collections of autonomous, non-synchronized, non-intelligent robots cooperating on a finite n-dimensional cellular space under distributed control. Limited communication exists only between adjacent robots. These robots operate autonomously and cooperate with others to accomplish predefined global tasks.

Hackwood and Beni [13] propose a model in which the robots are particularly simple but act under the influence of “signpost robots.” These signposts can modify the internal state of the swarm units as they pass by.

Under the action of the signposts, the entire swarm acts as a unit to carry out complex behaviors. Self-organization is realized via a rather general model whose most restrictive assumption is the cyclic boundary condition. The model requires that sensing swarm "circulate" in a loop during its sensing operation.

The behavior-based control strategy put forward by Brooks [14] is quite well known and it has been applied to collections of simple independent robots, usually for simple tasks. Other authors have also considered how a collection of simple robots can be used to solve complex problems. Ueyama et al.[15] propose a scheme whereby complex robots are organized in tree-like hierarchies with communication between robots limited to the structure of the hierarchy.

Mataric [16] describes experiments with a homogeneous population of robots acting under different communication constraints. The robots either act in ignorance of one another, are informed by one another, or intelligently (cooperate) with one another. As inter-robot communication improves, more and more complex behaviors are possible.

Swarm robots are more than just networks of independent agents, they are potentially reconfigurable networks of communicating agents capable of coordinated sensing and interaction with the environment. Considering the variety of possible designs of groups mobile robots, Dudek et al.[12] present a swarm-robot taxonomy of the different ways in which such swarm robots can be characterized. It helps to clarify the strengths, constraints and tradeoffs of various designs. The dimensions of the taxonomic axes are swarm size, communication range, topology, bandwidth, swarm reconfigurability, unit processing ability, and composition. For each dimension, there are some key sample points. For instance, swarm size includes the cases of single agent, pairs, finite sets, and infinite numbers. Communication ranges include none, close by neighbors, and "complete" where every agent communicate with every other agent. Swarm composition can be homogeneous or heterogeneous (i.e. with all the same agents or a mix of different agents). We can apply this swarm taxonomy to the above swarm models. For example, Hackwood and Beni's model [13] has multiple agents in its swarm, nearby communication range, broadcast communication topology, free communication bandwidth, dynamic swarm reconfigurability, heterogeneous composition, and its agent processing is Turing machine equivalent [12].

As the research on decentralized autonomous robotics systems has developed, several areas have received increasing attention including modeling of swarms, agent planning or decision making and resulting group behavior, and the evolution of group behavior. The latter two can be seen as part of the branch of distributed artificial intelligence since several agents coordinate or cooperate to make decisions. There are several optimization methods proposed for the group behavior. Fukuda et al.[17] introduced a distributed genetic algorithm for distributed planning in a cellular robotics system. They also proposed a concept of self-recognition for the decision making and showed the learning and adaptation strategy [18]. There are also other algorithms proposed.

1.3 Evaluation of Swarm Intelligent System

Although many studies on swarm intelligence have been presented, there are no general criteria to evaluate a swarm intelligent system's performance. Fukuda et al.[19] try to make an evaluation based on the flexibility, which is essentially a robustness property. They proposed measures of fault tolerance and local superiority as indices. They compared two swarm intelligent systems via simulation with respect to these two indices. There is a significant need for more analytical studies.

2 Stability of Swarms

2.1 Biological Models

In biology, researchers proposed "continuum models" for swarm behavior based on non-local interactions [20]. The model consists of integro-differential advection-diffusion equations, with convolution terms that describe long range attraction and repulsion. They found that if density dependence in the repulsion term is of a higher order than in the attraction term, then the swarm has a constant interior density with sharp edges as observed in biological examples. They did linear stability analysis for the edges of the swarm.

2.2 Characterizations of Stability

There are several basic principles for swarm intelligence, such as the proximity, quality, response diversity, adaptability, and stability. Stability is a basic property of swarms since if it is not present, then it is typically impossible for the swarm to achieve any other objective. Stability characterizes the cohesiveness of the swarm as it moves. How do we mathematically define if swarms are stable? Relative velocity and distance of adjacent members in a group can be applied as a criteria. Also, no matter whether it is a biological or mechanical swarm, there must exist some attractant and repellant profiles in the environment so that the group can move so as to seek attractants and avoid repellants. We can analyze the stability of swarm by observing whether swarms stay cohesive and converge to equilibrium points of a combined attractant/repellant profile.

2.3 Overview of Stability Analysis of Swarms

Stability of swarms is still an open problem. We searched the current literature and found that there is very little work done in this area. We overview this work next.

Jin et al.[21] proposed the stability analysis of synchronized distributed control of 1-D and 2-D swarm structures. They prove that synchronized swarm structures are stable in the sense of Lyapunov with appropriate weights in the sum of adjacent errors if the vertical disturbances vary sufficiently more slowly than the response time of the servo systems of the agents. The convergence under total asynchronous distributed control is still an open problem. Convergence of simple asynchronous distributed control can be proven in a way similar to the convergence of discrete Hopfield neural network. Beni [22] proposed a sufficient condition for the asynchronous convergence of a linear swarm to a synchronously achievable configuration since a large class of distributed robotic systems self-organizing tasks can be mapped into reconfigurations of patterns in swarms. The model and stability analysis in [21, 22] is, however, quite similar to the model and proof of stability for the load balancing problem in computer networks [23].

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