SWARM INTELLIGENCE

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Contents

Summary

This chapter provides an introduction to Swarm Intelligence (SI), a discipline dealing with artificial and natural systems studying the collective behaviors of social insects or animals. SI represents a new concept of Artificial Intelligence and is becoming increasingly popular in recent years. Nature provides many inspirations for the development of SI techniques. These SI techniques have shown remarkable capabilities on solving problems that are often difficult to handle by conventional computational techniques. In an SI system, although there is a lack of centralized control, the system at the swarm level exhibits complex and self-organizing behaviors. This is often the result of local interactions among individuals in the swarm as well as individuals with the environment, based on very simple interaction rules.

This chapter will first provide readers an overview on SI and how it complements the traditional definition of Artificial Intelligence. Several biological examples as inspirations for SI techniques will be provided, along with the SI metaphor of the human society. The application of SI principles to optimization is in particular prevalent among its many application areas. This chapter will focus on providing a detailed account on one of the most popular SI techniques, Particle Swarm Optimization (PSO). In particular, the chapter will present the canonical PSO and its variants, and provide an illustration of swarm dynamics through a simplified PSO. The chapter will also discuss several popular PSO application areas and its recent theoretical development.

1. Introduction

1.1. Swarm Intelligence

Swarm Intelligence refers to a family of Artificial Intelligence techniques that are inspired by the collective behaviors exhibited by social insects, animals, as well as human societies. Many such phenomena can be observed in nature, such as ant foraging behaviors, bird flocking, fish schooling, animal herding, and many more. Even though individual ants are simple insects and do not exhibit sophisticated behavior, many ants working together can achieve fairly complex tasks. An SI system typically consists of a population of individuals. These individuals are usually very simple agents that on their own do not exhibit complex behaviors. However, complex global patterns may emerge from interactions between these agents and the agents with the environment. An intriguing property of a SI system is its ability to behave in a complex and self-organized way without any specific individual taking control of everything. One definition on Swarm Intelligence provided by Kennedy (2006), the inventor of Particle Swarm Optimization, captures very nicely the essence of SI:

> "*Swarm intelligence refers to a kind of problem-solving ability that emerges in the interactions of simple information processing units. The concept of a swarm suggests multiplicity, stochasticity, randomness, and messiness, and the concept of intelligence suggests that the problem-solving method is somehow successful. The information-processing units that compose a swarm can be animate, mechanical, computational, or mathematical; they can be insects, birds, or human beings; they can be array elements, robots, or standalone workstations; they can be real or imaginary. Their coupling can have a wide range of characteristics, but there must be interaction among the units*."

SI techniques are problem solving techniques mimicking these sorts of social behaviors that we observe in nature. In essence, the problem solving ability of a SI technique is derived from the interactions among many simple information processing units (or agents). The term of Swarm Intelligence was first coined by Beni (1989) in the context of cellular robotic systems. Since then, the term has been used in a much broader research field (Blum and Merkle 2008).

1.2. A Broaden Concept of Intelligence

Traditionally intelligence has been considered as a trait of an individual. Kennedy and Eberhart (2001) remarked "*The early AI researchers had made an important assumption, so fundamental that it was never stated explicitly nor consciously acknowledged. They assumed that cognition is something inside an individual's head. An AI program was modeled on the vision of a single disconnected person, processing information inside his or her brain, turning the problem this way and that, rationally and coolly*". SI is a broaden concept of intelligence as it emphasizes the fact that intelligence should be modeled in a social context, as a result of interaction with one another. Intelligence should be seen as a collective entity rather than a single isolated one.

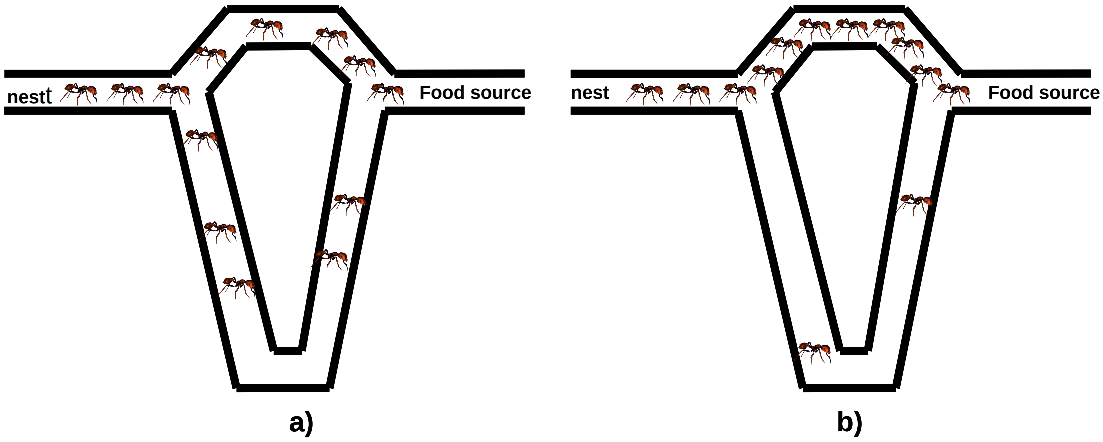

Figure 1. The double-bridge experiment: ants find the shorter path of the two between the nest and the food source; a) at the start, b) after some period, more ants choose the shorter path.

Figure 2. Flock of birds in flight (public domain image picture)**.**

1.3. Biological Examples

There are abundances of examples of social behaviors among insects and animals in nature that exhibit emergent intelligent properties. Following are just a few examples:

Ants exhibit interesting path-finding behaviors as they go out searching for food. A well known biological example is the double-bridge experiment, where two bridges of different lengths are placed between the ant nest and the food source (Figure 1). The ants are set out to reach the food source and bring the food back to the nest. Since ants leave pheromone trails as they move around, the path with more ants passed over it will have a higher intensity level of pheromone than the path with fewer ants visited. Although at the start of foraging, there is an equal probability of going along either of the two bridges (Figure 1a). After a certain period of time, as more ants come back via the shorter path of the two, the intensity level of pheromone on the shorter path increases. Because ants tend to follow the path with a higher intensity level of pheromone, there will be more and more ants choosing the shorter path to reach the food source. Eventually almost all ants would have converged on the shorter path (Figure 1b). It is remarkable that though no single ant knows about how to find the shorter path, many ants working together manage to achieve the task.

Birds fly in flocks to increase their chance of survival, finding food sources, and avoiding predators. By staying in a flock, birds gain several benefits. One major benefit is the so called “safety-in-number,” since if a predator approaches the flock, it is more likely to be seen by at least some of the birds in the flock than if a bird is just on its own. The alarm message can be quickly passed onto other birds in the vicinity, and soon to the entire flock. Staying in a flock also serves as a distraction, as the predator may struggle to single out any specific bird. Birds in a flock are more efficient in foraging - if any bird spots the food location and dive towards it, this information can be passed onto others quickly, thus the whole flock benefits. Flying in a flock following a certain pattern also improves the efficiency of the flight, due to better aerodynamics (Figure 2).

Many species of fish swim in schools so as to minimize their energy consumption and to escape from predators’ attack. Fish schooling often refers to the fact that fish swim in groups in a highly coordinated manner, e.g., in the same direction. A fish school may appear to take on a life of its own, as they move in unison like one single entity. It is amazing to see hundreds of fish change the direction or speed almost at the same exact instant. By staying in a school, each individual fish can look out for one another, helping them to avoid predators’ attack. By swimming in a certain formation following one another, fish can reduce their body friction with water thereby keeping energy consumption at a very low level.

Termites build sophisticated domed structures as a result of decentralized control. Individual termites participate in building a dome by following some very simple rules. For example, termites carry dirt in their mouths, and move in the direction of the strongest pheromone intensity, and then deposit the dirt where the smell is strongest. Initially termites are in random movements and only a number of small pillars are built. These pillars also happen to be the places visited by a larger number of termites, thereby the pheromone intensity being higher here. As more termites deposit their loads in a place, the more attractive this place is to other termites, resulting in a positive feedback loop. Since the deposit tend to be made on the inner side of the pillars, more and more build-up is formed on the inward facing side, eventually resulting in an arch.

Honey bees perform waggle dances to inform other bees about the superb sites of food sources. Honey bees use dance as a mechanism to convey information about the direction and distance of the food source. Dancing honey bees adjust both duration and the vigor of the dance to inform other bees about the profitability of the food source. The duration of the dance is measured by the number of waggle phases, while the vigor is measured by the time interval between waggle phases. The larger number of waggle phases, the more profitable the food source is, hence more bees will be attracted to it. More examples can be found from Blum and Merkle (2008).

1.4. Human Social Behaviors

Swarm Intelligence can be also observed in the human society. People learn from each other. Knowledge spreads from person to person. Culture emerges from populations. Human society has this remarkable ability to self-organize and adapt. A city like New York has several hundreds of bakeries to supply breads on a daily basis. No one dictates where exactly these bakeries should be located. Yet, these bakeries manage to do a good job to cater for the people living there. As a psychologist, Kennedy (Kennedy and Eberhart 2001) describes that the human society operates at three different levels, from individuals, to groups, to cultures: 1) Individuals learn locally from their neighbors. People interact with their neighbors and share insights with each other; 2) Group-level processes emerge as a result of the spread of knowledge through social learning. Regularities in beliefs, attitudes and behaviors across populations can be observed. A society is a self-organizing entity, and its global properties cannot be predicted from its constituent individuals; 3) Culture optimizes cognition. Locally formed insights and innovations are transported by culture to faraway individuals. Combination of various knowledge results in even more innovations.

1.5. Application of Swarm Intelligence Principles

The principles of SI have been predominantly applied to optimization, and as a result, inspired researchers to develop many new optimization algorithms (Blum and Li 2008). Among these algorithms, two most representative examples are Particle Swarm Optimization (Kennedy and Eberhart 2001) and Ant Colony Optimization (Dorigo, *et al*., 1996). The application of SI principles goes beyond just optimization though. For example, a new field of research, so called swarm robotics, is formed where physical robots are designed in such a way that they can collaborate to achieve tasks that are beyond the capability of any individual robot. This chapter will focus on introducing Particle Swarm Optimization (PSO), an increasingly popular SI optimization technique in recent years. Readers interested in general SI techniques could find a wealth of information from the following references (Bonabeau, *et al.*, 1999; Kennedy and Eberhart 2001).

2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) was originally proposed by James Kennedy and Russell Eberhart (Kennedy and Eberhart 1995). PSO is a meta-heuristic optimization technique modeled on the social behaviors observed in animals, insects and humans. Since its inception, PSO has enjoyed a wide acceptance among researchers and practitioners as a robust and efficient technique for solving difficult optimization problems. PSO was largely based on a key insight on human social behavior and cognition, as remarked by Kennedy: "*people learn to make sense of the world by talking with other people about it*" (Kennedy 2006). This simple yet remarkable observation allowed Kennedy and Eberhart to go on to design a computer program that encodes a population of candidate solutions and be able to refine these solutions iteratively through interactions among themselves, obtaining good suggestions from their neighbors, and making adjustment in order to improve further.

2.1. Introduction

In PSO, individual particles of a swarm represent potential solutions, which move through the problem search space seeking an optimal (or good enough) solution. The particles broadcast their current positions to neighboring particles. Through some random perturbation, the position of each particle is adjusted according to its velocity (i.e., rate of change) and the difference between its current position and the best position found by its neighbors, as well as the best position it has found so far, respectively. As the model is iterated, the swarm focuses more and more on an area of the search space containing high-quality solutions. The swarm as a whole is alike a flock of birds collectively searching for food. As time goes on, the flock gradually converges onto the food location. Locating an optimal solution in the search space is achieved by a collective effort through many particles interacting with each other.

In PSO, each particle's velocity is updated iteratively through its personal best position (i.e., the best position found by the particle so far), and the best position found by particles in its neighborhood. As a result, each particle searches around a region defined by its personal best position and the best position from its neighborhood. If we use $\mathbf{v}_i$ to denote the velocity of the i-th particle in the swarm, $\mathbf{x}_i$ to denote its position, $\mathbf{p}_i$ to denote the personal best position and $\mathbf{p}_{\mathrm{g}}$ the best position found by particles in its neighborhood. $\mathbf{v}_i$ and $\mathbf{x}_i$ in the original PSO algorithm are updated according to the following two equations (Kennedy and Eberhart 1995):

$$\mathbf{v}_i \leftarrow \mathbf{v}_i + \Phi_1 \otimes (\mathbf{p}_i - \mathbf{x}_i) + \Phi_2 \otimes (\mathbf{p}_{\mathrm{g}} - \mathbf{x}_i) \tag{1}$$

$$\vec{x} \leftarrow \vec{x} + \vec{v} \; \mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i \tag{2}$$

where $\Phi_1 = c_1\mathbf{R}_1$ and $\Phi_2 = c_2\mathbf{R}_2$. $\mathbf{R}_1$ and $\mathbf{R}_2$ are two separate vectors comprising random values uniformly and independently generated in the range [0,1]. c_1 and c_2 are acceleration coefficients. The symbol $\otimes$ denotes point-wise vector multiplication. Eq. (1) shows that the velocity term $\mathbf{v}_i$ of a particle is determined by three parts, the "momentum", the "cognitive", and the "social" part. The "momentum" term $\vec{v}$ represents the previous velocity term which is used to carry the particle in the direction it has traveled so far; the "cognitive" part, $\Phi_1 \otimes (\mathbf{p}_i - \mathbf{x}_i)$ represents the tendency of the particle to return to the best position it has visited so far; the "social" part, $\Phi_2 \otimes (\mathbf{p}_{\mathrm{g}} - \mathbf{x}_i)$, represents the tendency of the particle to be attracted towards the position of the best position found by the entire neighborhood.

Position $\mathbf{p}_{\mathrm{g}}$ in the "social" part is the best position found in the neighborhood of the i-th particle. Particles in a swarm can be mapped onto different communication structures or neighborhood topologies, which can be used to control information propagation between particles. A neighborhood topology can be thought of as a social network. Examples of neighborhood topologies include fully-connected, ring, star, and von

Neumann, etc (see Figure 3). Constricted information propagation as a result of using small neighborhood topologies such as von Neumann has been shown to perform better on complex problems, whereas larger neighborhoods generally perform better on simpler problems (Mendes *et al.* 2004). Generally speaking, a PSO implementation that chooses $\mathbf{p}_g$ from within a restricted local neighborhood is referred to as *lbest* PSO, whereas choosing $\mathbf{p}_g$ without any restriction (hence from the entire swarm) results in a *gbest* PSO. Algorithm 1 summarizes the basic PSO algorithm.

Algorithm 1: The basic PSO algorithm (assuming minimization):

Randomly generate an initial swarm
repeat
  for each particle i **do**
    if $f(\mathbf{x}_i) < f(\mathbf{p}_i)$ **then** $\mathbf{p}_i \leftarrow \mathbf{x}_i$
    if $f(\mathbf{x}_i) < f(\mathbf{p}_g)$ **then** $\mathbf{p}_g \leftarrow \mathbf{x}_i$
    update velocity (see Eq. (1))
    update position (see Eq. (2))
  end for
until termination criterion is met

Generally speaking if we do not have any prior knowledge of a problem, then a particle's position $\mathbf{x}_i$ is initialized randomly in the search space. The size of the velocity term $\mathbf{v}_i$ is often randomly initialized in the range from 0 to that of half of the search space (Clerc 2006). The direction of $\mathbf{v}_i$ is set randomly by setting each dimension of $\mathbf{v}_i$ to either positive or negative (50% probability each). Setting $\mathbf{v}_i$ this way is to ensure that the particle is propelled to move in some random direction even from the beginning of the optimization run. At the first iteration, the particle's personal best position $\mathbf{p}_i$ is set equal to $\mathbf{x}_i$, and from there onwards, $\mathbf{p}_i$ is updated with $\mathbf{x}_i$ only if the fitness of $\mathbf{x}_i$ is better than that of $\mathbf{p}_i$.

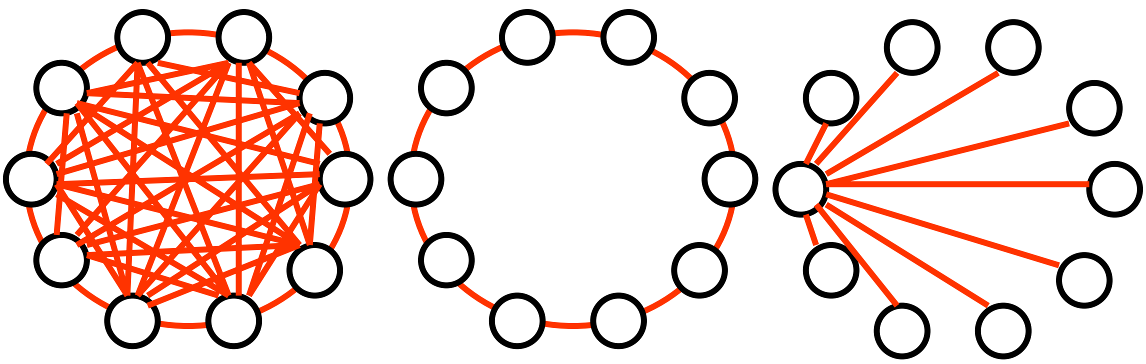

Figure 3. Neighborhood topologies: fully-connected, ring, and star (from left to right).

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Biographical Sketches

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