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Swarm Intelligence – A Survey

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***Abstract*: This paper gives a review on swarm intelligence and how the intelligence is applied to computer science. It mainly focuses on Particle Swarm Optimization (PSO), Ant Colony System (ACS), Stochastic Diffusion Search (SDS), Bacteria Foraging (BF), the Artificial Bee Colony (ABC), and so on. There are various areas how swarm intelligence can be applied to computer science. Controlling robots and unmanned vehicles, predicting social behaviors, enhancing the telecommunication and computer networks are few of its applications.**

***Keywords*: swarm intelligence(SI), PSO, ACS, SDS, BF, ABC**

1. Introduction

Swarm intelligence is an important concept in artificial intelligence and computer science with emergent properties. The essential idea of swarm intelligence algorithms is to employ many simple agents applying almost no rule which in turn leads to an emergent global behavior.

To put it in a simple way, swarm intelligence can be described as the collective behavior emerged from social insects working under very few rules. Self-organization is the main theme with limited restrictions from interactions among agents. Many famous examples of swarm intelligence come from the world of animals, such as birds flock, fish school and bugs swarm. The social interactions among individual agent help them to adapt to the environment more efficiently since more information are gathered from the whole swarm. This paper aims to introduce several well-known and interesting algorithms based on metaheuristic derived from nature and their applications in problem solving.

2. Social insects: swarm intelligence

Insects that live in colonies, like ants, bees, termites and wasps have inspired naturalists as well as poets for many years. "What is it that governs here? What is it that issues orders, foresees the future, elaborates plans and preserves equilibrium?" wrote Maeterlinck. In a social insect colony, a worker usually does not perform all tasks, but rather specializes in a set of tasks according to its morphology, age or chance. This division of labor among nestmate, whereby different activities are performed simultaneously by groups of specialized individuals.

The modeling of social insects by means of self-organization can help design artificial distributed problem-solving devices that self-organize to solve problems – swarm-intelligent systems. The goal of swarm intelligence is the design of multi agent intelligent systems by taking inspiration from the collective behavior of social insects and other animal societies such as fish schools, flocks of birds and etc.

A. *Self-organization*

The discovery that self-organization may be at work in social insects and also provides us with powerful tools to transfer knowledge about social insects to the field of intelligent system design. In effect, a social insect colony is a decentralized problem-solving system, comprised of many relatively simple interacting entities. The daily problems solved by a colony include finding food, building, repairing or extending a nest, efficiently dividing labor among individuals, efficiently feeding the brood, responding to external challenges, spreading alarm, etc.

Many of these problems have counterparts in computer science and engineering. One of the most important features of social insects is that they can solve these problems in a very flexible (allows to adaptation to changing environments) and robust way (empower the colony with the ability to function even though some individuals may fail to perform their tasks).

B. *The Individual Discrimination Capabilities*

Many social insects are able to discriminate between nestmates and non-nestmates. In an ant society individuals coming from different groups bear its own chemical identity and those individual present discrimination capabilities between different chemical profiles. However, at the collective level these groups may cooperate and act together. To understand this apparent contradiction, amplification is the main component of many collective phenomena in social insects. Such collective response is a generic property of social phenomena governed by amplification process.

3. Related Work

A. *Combinatorial Optimization (CO)*

Combinatorial optimizations are of high importance both for the scientific world as well as for the industrial world like telecommunication network design, artificial intelligence, shape optimization or computational biology. The research community has simplified many of these problems like traveling salesman problem, minimum spanning tree problem, etc. Generally, CO is a NP-hard problem can be defined as P =

(S, Ω, f) is an optimization problem where S is a search space defined over a finite set of discrete decision variables, Ω is a set of constraints among the variables and an objective function

F:s-> R+

that assigns a positive cost value to each of the objects s ε S. The goal is to find an object of minimal cost value. The search space S is defined as a set of discrete variables Xi where i = 1, 2,… n with values vi j ε Di = {vi 1 ,… vi |Di|}, that is, each assignment of Xi has a value vi j assigned from its domain Di. The set of feasible solutions SΩ is given by the elements of S that satisfy all the constraints in the set Ω.

4. Bee colony optimization algorithms

Bees have similar food collecting behaviors. Instead of pheromones, bees colony optimization algorithm relies on the foraging behavior of honey bees. At the first stage, some bees are sent out to look for promising food sources. After a good food source is located, bees return back to colony and perform a waggle dance to spread out 3 information about the source. Three pieces of information are included:1. distance, 2. direction, 3. quality of food source. The better the quality of food source, the more bees will be attracted. Therefore, the best food source emerges. The metaheuristic extracted from the foraging behaviors of bees can also be applied to solve combinatorial problems; especially problems involve global minimum or maximum.

5. Particle Swarm optimization Algorithm

Bird flocking and fish schooling are the inspirations from nature behind particle swarm optimization algorithms. It was first proposed by Eberhart and Kennedy. Mimicking physical quantities such as velocity and position in bird flocking, artificial particles are constructed to “fly” inside the search space of optimization problems.

However, different from the previous two algorithms using pheromone or feedback as tools to get rid of undesired solutions, particle swarm optimization algorithms updates the current solution directly. As you can tell from the following description of the framework of PSO algorithms, with fewer parameters, PSO algorithms are easy to implement and achieve global optimal solutions with high probability. Initially, a population of particles is distributed uniformly in the multi-dimension search space of the objective function of the optimization problem. Two quantities are associated with particles, a position vector ~xi and a velocity ~vi. At each time step, the velocities of particles will be updated according to the following formula:

$$\sim vi\ t+1 = v\ t\ i + r1 * \alpha(\sim b - \sim x\ t\ i\ ) + r2 * \beta(\sim n - \sim x\ t\ i\ )$$

where ~b is the global best location and ~n is the best location in the neighborhood of particle pi. Both α, β are learning parameters and r1, r2 are random parameters ranging from 0 to 1. The positions will be updated simply by

$$\sim x\ t+1\ i = \sim x\ t\ i + \sim v\ t+1\ i$$

The importance of including a neighborhood best location ~n for each particle is to avoid the swarm being trapped into a local minimum. This is where the social connection comes into play in particle swarm optimizations. The social connection topology is called swarm’s population topology. There are different types, for example, the gbest topology. With such a topology, particles are all attracted to the global best solution; therefore, it represents the fully connected social network.

6. Ant Colony Optimization Algorithms

The most recognized example of swarm intelligence in real world is the ants. To search for food, ants will start out from their colony and move randomly in all directions. Once an ant find food, it returns to colony and leave a trail of chemical substances called pheromone along the path. Other ants can then detect pheromone and follow the same path. The interesting point is that how often is the path visit by ants is determined by the concentration of pheromone along the path. Since pheromone will naturally evaporate over time, the length of the path is also a factor. Therefore, under all these considerations, a shorter path will be favored because ants following that path keep adding pheromone which makes the concentration strong enough to against evaporation. As a result, the shortest path from colony to foods emerges.

Many NP-hard problems in computer science, which are problems with exponential time worst case complexity, can be solved using ACO algorithms, such as the assignment problem category and the scheduling problem category. There are proofs that ACO algorithms will converge to these best-performing algorithms. However, the speed of convergence is unknown and the performance of ACO algorithms largely depend on if an optimal local search procedure can be found and this is very problem-specific.

7. Conclusions

The ant and bee colony optimization algorithms are based on metaheurisitic derived from their feedback systems: pheromones and waggle dances. The information accumulated from their collective behaviors guides each agent toward the optimal solution. Particle swarm optimization algorithms have the simplest framework, employing particles to search for optimal solution directly. With the help of social interactions and related population topologies, PSO algorithms are able to avoid local minimums and search for global optimal solution more efficiently. Cuckoo search is one of the most interesting algorithms. It mimics the brood parasitism of cuckoos.

By protecting better solutions and abandon undesired ones throughout evolution, the global optimal solution emerges. All of the four algorithms have rich applications in problem solving. They can be customized to deal with problems such as NP-hard problems, combinatorial optimization problems and numerical optimization problems. On the other hand, we should also note the limitations of swarm intelligence.

First of all, all swarm intelligence algorithms have parts that are problem-specific, for example, the performance of ant colony optimization algorithms largely depends on the local search subroutines and population topologies have influences on the performance of particle swarm optimization algorithms. Secondly, it is hard to analyze the computational complexity of these algorithms, therefore, it is difficult to tell whether a swarm intelligence algorithm will be suitable or 9 efficient for certain problems. Moreover, the famous "no free lunch theorem" by Wolpert and Macready questions the overall performance of swarm intelligence algorithms and argues that if we take an average over all problems, every optimization algorithm works equally well.

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