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A Profound Survey on Swarm Intelligence

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Abstract

Swarm Intelligence (SI) is the collective behavior of decentralized, self-organized systems, natural or artificial. The concept is employed in work on artificial intelligence. The inspiration often comes from nature, especially biological systems. The expression was introduced by Gerardo Beni and Jing Wang in 1989, in the context of cellular robotic systems. SI systems are typically made up of a population of simple agents or boids interacting locally with one another and their environment. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local, and to a certain degree random, interaction between such agents lead to the emergence of "intelligent" global behavior, unknown to the individual agents. Swarm Intelligence is a relatively new paradigm being applied in a host of research settings to improve the management and control of large numbers of interacting entities such as communications, computer and sensor networks, satellite constellations and more. Attempts to take advantage of this paradigm and mimic the behavior of insect swarms however often lead to many different implementations of SI. Natural examples of SI include ant colonies, bird flocking, animal herding, bacterial growth and fish schooling. This article provides a set of general principle of Swarm Intelligence.

Index Terms

Swarm intelligence, SI, self-organized, agents, ANN, GSA, IWD

1. Introduction

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. We call this kind of aggregate motion "swarm behavior". Recently the 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, engineer are increasingly interested in this king of swarm behavior since the resulting "Swarm Intelligence" can be applied in optimization , robotics, traffic patterns in transportation systems and military applications. High level view of a swarm suggests that the N agents in the swarm are cooperating to achieve some purposeful 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 action 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. For example, for a bird to participate in a flock, it only adjusts its movements to coordinate with the movements of flock mates, typically its "neighbor" 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 for birds in exploiting the eyes of every other bird).

2. Swarm Behavior Diagram

Figure: 1 Swarm Behavior

The swarming behavior of ants, bees, termites, and other social insects has implications far beyond the hive. Swarm intelligence – the collective behavior of independent agents, each responding to local stimuli without supervision – can be used to understand and model phenomena as diverse as blood clotting, highway traffic patterns, gene expression, and immune response, to name just a few swarm technology is providing useful in a wide range of applications including robotics and nanotechnology, molecular biology and medicine, traffic and crowd control, military tactics, and even interactive arts.

3. Particle Swarm Optimization

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling.

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithm (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutations. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called *lbest*. When a particle takes all the population as its topological neighbors, the best value is a global best and is called *gbest*. The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its p*best* and *lbest* locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *lbest* locations.

In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods.

Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

a. Artificial neural network and PSO

An artificial neural network (ANN) is an analysis paradigm that is a simple model of the brain and the back-propagation algorithm is the one of the most popular method to train the artificial neural network. Recently there have been significant research efforts to apply evolutionary computation (EC) techniques for the purposes of evolving one or more aspects of artificial neural networks. Evolutionary computation methodologies have been applied to three main attributes of neural networks: network connection weights, network architecture (network topology, transfer function), and network learning algorithms.

Most of the work involving the evolution of ANN has focused on the network weights and topological structure. Usually the weights and/or topological structure are encoded as a chromosome in GA. The selection of fitness function depends on the research goals. For a classification problem, the rate of mis-classified patterns can be viewed as the fitness value.

The advantage of the EC is:
1. EC can be used in cases with non-differentiable PE transfer functions and no gradient information available.
The disadvantages are:

1. The performance is not competitive in some problems.
2. Representation of the weights is difficult and the genetic operators have to be carefully selected or developed.

There are several papers reported using PSO to replace the back-propagation learning algorithm in ANN in the past several years. It showed PSO is a promising method to train ANN. It is faster and gets better results in most cases. It also avoids some of the problems GA met.

Here we show a simple example of evolving ANN with PSO. The problem is a benchmark function of classification problem: iris data set. Measurements of four attributes of iris flowers are provided in each data set record: sepal length, sepal width, petal length, and petal width. Fifty sets of measurements are present for each of three varieties of iris flowers, for a total of 150 records, or patterns.

A 3-layer ANN is used to do the classification. There are 4 inputs and 3 outputs. So the input layer has 4 neurons and the output layer has 3 neurons. One can evolve the number of hidden neurons. However, for demonstration only, here we suppose the hidden layer has 6 neurons. We can evolve other parameters in the feed-forward network. Here we only evolve the network weights. So the particle will be a group of weights, there are 4*6+6*3 = 42 weights, so the particle consists of 42 real numbers. The range of weights can be set to [-100, 100] (this is just a example, in real cases, one might try different ranges). After encoding the particles, we need to determine the fitness function. For the classification problem, we feed all the patterns to the network whose weights is determined by the particle, get the outputs and compare it the standard outputs. Then we record the number of misclassified patterns as the fitness value of that particle. Now we can apply PSO to train the ANN to get lower number of misclassified patterns as possible. There are not many parameters in PSO need to be adjusted. We only need to adjust the number of hidden layers and the range of the weights to get better results in different trials.

4. Applications

The applications of swarm principles to robots are called swarm robotics, while swarm intelligence refers to the more general set of algorithms.

A. Swarm Robots

Swarm robotics is currently one of the most important applications 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 task that would be impossible for a single robot to achieve. Swarm robots can be applied to many fields, such as manufacturing systems, spacecraft, inspection, maintenance, construction, agriculture, and medicine work.

Many different swarm models have been proposed. Beni 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.

Swarm robots are more than just networks of independent agents; they are potentially reconfigurable networks of communicating agents capable of coordinate sensing and interaction with the environment. Considering the variety of possible designs of group's mobiles robots. Dudek et al. presents 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 taxonomies axes are swarm size, communication range, topology, bandwidth, swarm reconfigurability, unit processing ability, and compositions. For each dimension, there are some key sample points. For instance, swarm size includes the cases of single agent, pairs, finite sets, and finite numbers. Communications 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 al the same agents or mix of different agents). We can apply this swarm taxonomy to the above swarm models. For example, Hackwood and Beni's model 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.

B. Crowd Simulations

Artists are using swarm technology as a means of creating complex interactive systems or simulating crowds.

Stanley and Stella in: Breaking the Ice was the first movie to make use of swarm technology for rendering, realistically depicting the movements of groups of fish and birds using the Boids system. Tim Burton's Batman Returns also made use of swarm technology for showing the movements of a group of bats. The Lord of the Rings film trilogy made use of similar technology, known as Massive, during battle scenes. Swarm technology is particularly attractive because it is cheap, robust, and simple.

Airlines have used swarm theory to simulate passengers boarding a plane. Southwest Airlines researcher Douglas A. Lawson used an ant-based computer simulation employing only six interaction rules to evaluate boarding times using various boarding methods

C. ANT Based Routing

The use of Swarm Intelligence in Telecommunication Networks has also been researched, in the form of Ant Based Routing. This was pioneered separately by Dorigo et al. and Hewlett Packard in the mid-1990s, with a number of variations since. Basically this uses a probabilistic routing table rewarding/reinforcing the route successfully traversed by each "ant" (a small control packet) which flood the network. Reinforcement of the route in the forwards, reverse direction and both simultaneously has been researched: backwards reinforcement requires a symmetric network and couples the two directions together; forwards reinforcement rewards a route before the outcome is known (but then you pay for the cinema before you know how good the film is). As the system behaves stochastically and is therefore lacking repeatability, there are large hurdles to commercial deployment. Mobile media and new technologies have the potential to change the threshold for collective action due to swarm intelligence

5. Algorithm

By the beginning of swarm research, the researcher is trying to make an algorithm which can make effective swarm behavior. There are many algorithms which have been proposed by researcher, and we will some key algorithm of swarm.

a. ANT Colony Optimization

Ant colony optimization is a class of optimization algorithms modeled on the action of ant colony, ACO methods are useful in problems that need to find paths to goals. Artificial 'ants' –simulation agents- locate optimal solutions by moving through a parameter space representing all possible solutions. Real ants lay down pheromones directing each other to resource while exploring there environment. The simulated 'ants' similarly record their positions and the quality of their solutions, so that in later simulation iterations more ants locate better solutions. One variation on this approach is the bee's algorithm, which is more analogous to the forging patterns of the honey bee.

b. Artificial BEE Colony Algorithm

Artificial bee colony (ABC) algorithm is a swarm based meta-heuristic algorithm introduced by Karaboga in 2005, and simulates the foraging behavior of honey bees. The ABC algorithm has three phases: employed bee, onlooker bee and scout bee. In the employed bee and onlooker bee phases, bees exploit the sources by local searches in the neighborhood of the solutions selected based on deterministic selection in the employed bee phase and the probabilistic selection in the onlooker bee phase. In the scout bee phase which is an analogy of abandoning exhausted food sources in the foraging process, solution that are beneficial anymore for search progress are abandoned, and new solutions are inserted instead of them to explore new regions in the search space. The algorithm has a good-balanced exploration and exploitations ability.

c. GSA

Gravitational search algorithm (GSA) is constructed based on the law of gravity and the notion of mass interactions. The GSA algorithm uses the theory of Newtonian physics and its searcher agents are the collection of masses. In GSA, there is an isolated system of masses. Using the gravitational force, every mass in the system can see the situation of other masses. The gravitational force is therefore a way of transferring information between different masses. In GSA, agents are considered as objects and their performance is measured by their masses. All these objects attract each other by a gravity force, and this force causes a movement of all objects globally towards the objects with heavier masses. The heavy masses correspond to good solutions of the problem. The position of the agent corresponds to a solution of the problem, and its mass is determined using a fitness function. By lapse of time, masses are attracted by the heaviest mass. We hope that this mass would present an optimum solution in the search space. The GSA could be considered as an isolated system of masses. It is like a small artificial world of masses obeying the Newtonian laws of gravitation and motion. A multi-objective variant of GSA, called Non-dominated Sorting Gravitational Search Algorithm (NSGSA), was proposed by Nobahari and Nikusokhan in 2011.

d. Intelligent Water Drop

Intelligent Water Drops algorithm (IWD) is a swarm-based nature-inspired optimization algorithm, which has been inspired by natural rivers and how they find almost optimal paths to their destination. These near optimal or optimal paths follow from actions and reactions occurring among the water drops and the water drops with their riverbeds. In the IWD algorithm, several artificial water drops cooperate to change their environment in such a way that the optimal path is revealed as the one with the lowest soil on its links. The solutions are incrementally constructed by the IWD algorithm. Consequently, the IWD algorithm is generally a constructive population-based optimization algorithm.

e. River Formation Dynamics

River formation dynamics (RFD) is a heuristic method similar to ant colony optimization (ACO). In fact, RFD can be seen as a gradient version of ACO, based on copying how water forms rivers by eroding the ground and depositing sediments. As water transforms the environment, altitudes of places are dynamically modified, and decreasing gradients are constructed. The gradients are followed by subsequent drops to create new gradients, reinforcing the best ones. By doing so, good solutions are given in the form of decreasing altitudes. This method has been applied to solve different NP-complete problems (for example, the problems of finding a minimum distances tree and finding a minimum spanning tree in a variable-cost graph). The gradient orientation of RFD makes it especially suitable for solving these problems and provides a good tradeoff between finding good results and not spending much computational time. In fact, RFD fits particularly well for problems consisting in forming a kind of covering tree.

f. Stochastic Diffusion Search

Stochastic diffusion search (SDS) is an agent-based probabilistic global search and optimization technique best suited to problems where the objective function can be decomposed into multiple independent partial-functions. Each agent maintains a hypothesis which is iteratively tested by evaluating a randomly selected partial objective function parameterized by the agent's current hypothesis. In the standard version of SDS such partial function evaluations are binary, resulting in each agent becoming active or inactive. Information on hypotheses is diffused across the population via inter-agent communication. Unlike the stigmergic communication used in ACO, in SDS agents communicate hypotheses via a one-to-one communication strategy analogous to the tandem running procedure observed in some species of ant. A positive feedback mechanism ensures that, over time, a population of agents stabilizes around the global-best solution. SDS is both an efficient and robust search and optimization algorithm, which has been extensively mathematically described.

6. Advantages of Swarm Intelligence

There are many advantages of swarm intelligence. Such as,

1. Flexibility is a group that can be compatible in a dynamic environment.
2. Robustness, is irrespective of individual misbehavior or loss, the group can accomplish its tasks.
3. Self-organization is inherent parallelism or distributed action with little or no supervision.

7. Conclusions

Swarm intelligence provides a distributive approach to the problem solving mimicking the very simple natural process of cooperation. According to survey many solutions that had been previously solved using AI approach like genetic algorithm neural network are also solve able by this approach also. Due to its simple architecture and adaptive nature like ACO has it is more likely to be seen much more in the future.

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