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SURVEY ARTICLE

A Survey on Swarm Intelligence Algorithms

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Abstract— This paper surveys the intersection of fascinating and increasingly popular domain: swarm intelligence. Swarm intelligence is a relatively new subfield of artificial intelligence which studies the emergent collective intelligence of groups of simple agents. It is based on social behaviour that can be observed in nature, such as ant colonies, flocks of birds, fish schools and bee hives, where a number of individuals with limited capabilities are able to come to intelligent solutions for complex problems. In recent years the swarm intelligence paradigm has received widespread attention in research, mainly as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). Most swarm intelligence algorithms were devised for continuous optimization problems. This survey aims at providing an updated review of research of swarm intelligence algorithms for discrete optimization problems, comprising combinatorial or binary. The biological inspiration that stimulated the creation of each swarm algorithm is introduced, and later and encoding methods used to adapt each algorithm for complex problems. Methods are compared for different classes of problems and a critical analysis is provided, pointing to future trends.

Keywords: Swarm Intelligence combinatorial problem; Ant Colony Optimization (ACO); Particle Swarm Optimization (PSO)

I. INTRODUCTION

Swarm intelligence studies the collective behaviour of systems composed of many individuals interacting locally with each other and with their environment. Swarms inherently use forms of decentralized control and self-organization to achieve their goals (Dorigo, 2007). Researchers in computer science have developed swarm-based systems in response to the observed success and efficiency of swarms in nature to solve difficult problems. In such biological swarms, the individuals (ant, bee, termite, bird or fish) are by no means complete engineers, but instead are simple creatures with limited cognitive abilities and limited means to communicate. Yet the complete swarm exhibits intelligent behaviour, providing efficient solutions for complex problems such as predator evasion and shortest path finding.

Research in SI started in the late 1980s. Besides the applications to conventional optimization problems, SI can be employed in library materials acquisition, communications, medical dataset classification, dynamic control, heating system planning, moving objects tracking, and prediction. Indeed, SI can be applied to a variety of fields in fundamental research, engineering, industries, and social sciences. The main objective of this special issue is to provide the readers with a collection of high quality research articles that address the broad challenges in application aspects of swarm intelligence and reflect the emerging trends in state-of-the-art algorithms.

1. Swarm Algorithms

Many models in computer science have been inspired by nature, but not all of them may be considered swarm intelligence. Swarms generally involve movement of individuals through a demonstration space, and not all nature inspired algorithms do this. For example, artificial neural networks and evolutionary algorithms are geographically inspired algorithms (based on principles of neuroscience and evolution, respectively), and have been used for data mining, but they are not swarm intelligence.

1.1. Particle Swarm Optimization

The robustness of PSO results from its use of swarm intelligence to search for the best solution to a complex problem. The swarm intelligence can be described as a system that automatically evolves by simulates the social behaviour of organisms, e.g., the social behaviour of knowledge sharing. By sharing valuable information, the behaviours of individuals in a swarm are optimized to achieve a certain objective. In PSO, an individual is considered a particle, which is a vector in the problem space. The information for the particle includes knowledge gained from its previous experience and knowledge gained from the swarm. The value of the particle, which is estimated by the objective function, is used to update its information and to optimize the objective of the swarm. Therefore, the swarm can converge to develop good resolution in local regions of the problem space; the common objective can also be updated when one particle finds a better objective so that the particle can lead the swarm in exploring a different region of the problem space. These superior search characteristics have made PSO the most popular evolutionary algorithm in several fields.

1.2. Cuckoo Search Algorithm

For simplicity in describing our new Cuckoo Search, we now use the following three idealized rules:
1) Each cuckoo lays one egg at a time, and dump its egg in randomly chosen nest;
2) The best nests with high quality of eggs will carry over to the next generations;
3) The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability pa [0,1].
In this case, the host bird can either throw the egg away or abandon the nest, and build a completely new nest. For simplicity, this last assumption can be approximated by the fraction pa of the n nests are replaced by new nests (with new random solutions).

1.3. Gravitational Search Algorithm

To overcome the problems of parameter convergence and stagnation associated with PSO (Ling et al., 2008; Biswal et al., 2009), this paper adopts one recently proposed novel evolutionary optimization algorithm known as gravitational search algorithm (GSA) for the purpose of IIR digital filter design. In GSA, agents/solution vectors are considered as objects and their performances are measured by their masses. All these objects attract each other by the gravity forces, and these forces produce a global movement of all objects towards the objects with heavier masses. Hence, masses cooperate using a direct form of communication through gravitational forces. The heavier masses (which correspond to better solutions) move more slowly than lighter ones. This guarantees the exploitation step of the algorithm.

Three kinds of masses are defined in theoretical physics:

(a) Active gravitational mass (Ma) is a measure of the strength of the gravitational field due to a particular object. Gravitational field of an object with small active gravitational mass is weaker than the object with more active gravitational mass.

(b) Passive gravitational mass (Mp) is a measure of the strength of an object's interaction with the gravitational field. Within the same gravitational field, an object with a smaller passive gravitational mass experiences a smaller force than an object with a larger passive gravitational mass.

(c) Inertial mass (Mi) is a measure of an object's resistance to changing its state of motion when a force is applied. An object with large inertial mass changes its motion more slowly, and an object with small inertial mass changes it rapidly.

1.4. Firefly Algorithm

Firefly Algorithm (FA or FFA) developed by Xin-She Yang at Cambridge University in 2007, use the following three idealized rules:
1. All the fireflies are unisex so it means that one firefly is attracted to other fireflies irrespective of their sex.
2. Attractiveness and brightness are proportional to each other, so for any two flashing fireflies, the less bright one will move towards the one which is brighter. Attractiveness and brightness both decrease as their distance increases. If there is no one brighter than other firefly, it will move randomly.
3. The brightness of a firefly is determined by the view of the objective function.

For a maximization problem, the brightness is simply proportional to the value of the objective function. Other forms of the brightness could be defined in an identical way to the fitness function in genetic algorithms.

1.5. Roach Infestation Optimization

In RIO algorithm, cockroaches' agents are defined using three simple behaviours:
1. Cockroaches search for the darkest locality in the search space and the condition value is directly proportional to the level of darkness.
2. Cockroaches hang out with nearby cockroaches.
3. Third behaviour is cockroaches sometimes become hungry and leave the friendship to search for food.

1.6. Bat Algorithm

For simplicity, use the following approximate or idealized rules [34]:
1. All bats use echolocation to sense distance, and they also knows the difference between food/prey and background barriers in some magical way;
2. Bats fly randomly with velocity vi at position xi with a fixed frequency f min, varying wavelength λ and loudness A0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission r ∈ [0, 1], depending on the proximity of their target;
3. Although the loudness can vary in many ways, we assume that the loudness varies from a large (positive) A0 to a minimum constant value A min.

1.7. Glow-worm Swarm Optimization Algorithm

The Glow-worm Swarm Optimization (GSO) algorithm was first presented by as an application to collective robotics. In this algorithm, each glow-worm uses a probabilistic mechanism to select a neighbor that has a luciferin value associated with him and moves towards it. Glow-worms are attracted to neighbours that glow brighter (that is, glow-worms that have more luciferin). The movements are based only on local information and selective neighbour interactions. This enables the swarm to divide into disjoint subgroups that can converge to multiple optima of a given multimodal function.

1.8. Bee Algorithm

The Bee Algorithm (BA1) was first applied to continuous optimization functions and, later for scheduling jobs (Pham et al ., 2007a) and binary data clustering (Pham et al ., 2007b). In these papers, the authors used discrete encoding, ensuring that possible solutions would be valid. The BA1 also inspired Bahamish et al . (2008) to create a discrete encoding for the Protein Tertiary Structure Prediction (PTSP), a difficult combinatorial optimization problem. Bees that have the highest fitness are chosen as "selected bees" and sites visited by them (elite sites) are chosen for neighborhood search. The algorithm conducts searches in the neighbourhood of the selected sites, assigning more bees to search near to the best sites (recruitment).
A Binary BA1 (BBA) was proposed by Xu et al . (2010) focusing on a two-level Distribution Optimization Problem (DOP), which expressed the agents (bees) as two binary matrices, representing how to assign each bee to its course or mission.

1.9. Other Swarm Intelligence Algorithms

The Gravitational Search Algorithm (GSA) was applied by Li et al. with the RK discretization method transforming the continuous solutions into discrete ones. Chen et al. (2011) also applied the GSA to solve the TSP with RK, but integrating the simulated annealing technique (SA) into the algorithm for accomplishing local search. A binary implementation of GSA was proposed by Papa et al. (2011), together with the SF method, and used for a feature selection problem. Nakamura et al. proposed a binary version of the Bat Algorithm (BA) to solve the hypercube problem, where each bat is a set of binary coordinates. The equation to update the position of the original BA is replaced by the SF method of discretization. Xiangyang et al . (2011) proposed the Artificial Fish School Algorithm (AFSA) to solve KP using the RK method. He et al .(2009) proposed the AFSA mapped into the integer space directly, using a method that ensures that the candidate solution stays in integer space throughout the optimization process.

II. CONCLUSIONS

This work presents classification of the most recent development in swarm optimization. In the beginning two main algorithms of swarm optimization were in picture ant colony optimization and particle swarm optimization. Swarm intelligence is a new domain of Artificial Intelligence. A few evolutionary algorithms have been used with multi-objective functions. Swarm optimization algorithms such as ant colony, particle swarm optimization, bee based algorithms and firefly algorithm have been used in wide variety of engineering problems. Other Swarm based algorithms are also used in mining, identification of genes and DNAs.

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