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New Advancements in Swarm Algorithms: Operators and Applications

Springer

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Preface

The most common term for methods that employ stochastic schemes to produce search strategies is metaheuristics. In general, there not exist strict classifications of these methods. However, several kinds of algorithms have been coined depending on several criteria such as the source of inspiration, cooperation among the agents or type of operators.

From the metaheuristic methods, it is considered a special set of approaches which are designed in terms of the interaction among the search agents of a group. Members inside the group cooperate to solve a global objective by using local accessible knowledge that is propagated through the set of members. With this mechanism, complex problems can be solved more efficiently than considering the strategy of single individual. In general terms, this group is referred to as a swarm, where social agents interact with each other in a direct or indirect manner by using local information from the environment. This cooperation among agents produces an effective distributive strategy to solve problems. Swarm intelligence (SI) represents a problem-solving methodology that results from the cooperation among a set of agents with similar characteristics. During this cooperation, local behaviors of simple elements produce the existence of complex collective patterns.

The study of biological entities such as animals and insects which manifest a social behavior has produced several computational models of swarm intelligence. Some examples include ants, bees, locust swarms, spiders and bird flocks. In the swarm, each agent maintains a simple strategy. However, due to its social behavior, the final collective strategy produced by all agents is usually very complex. The complex operation of a swarm is a consequence of the cooperative behavior among the agents generated during their interaction.

The complex operation of the swarm cannot be reduced to the aggregation of behaviors of each agent in the group. The association of all simple agent behaviors is so complex that usually is not easy to predict or deduce the global behavior of the whole swarm. This concept is known as emergence. It refers to the process of produce complex behavioral patterns from the iteration of simple and unsophisticated strategies. Something remarkable is that these behavioral patterns appear without the existence of a coordinated control system but emerge from the exchange of local information among agents. Therefore, there subsists a close relationship between individual and collective behavior. In general, the collective behavior of agents determines the behavior of the swarm. On the other hand, swarm behavior is also strongly influenced by the conditions under which each agent executes its operations.

The operations of each agent can modify its own behavior and the behavior of other neighbor agents, which also alters the global swarm performance. Under such conditions, the most significant element of swarm intelligence is the model of interaction or cooperation among the agents. Cooperation in biological entities that operate as swarm systems happens in different mechanisms from which social interaction represents the most important. This social interaction can be conducted through physical contact, visual information, audio messages, or chemical perceptual inputs. Examples of cooperation models in nature are numerous, and some examples include the dynamical task assignation performed in an ant colony, without any central control or task coordination. The adoption of optimal spatial patterns builds by the self-organization in bird flocks and fish in schools. The hunting strategies developed by predators. The purpose of computational swarm intelligence schemes is to model the simple behaviors of agents and its local interactions with other neighboring agents to perform an effective search strategy for solving optimization problems.

One example is the particle swarm optimization (PSO) which models two simple actions. Each agent (1) moves toward the best agent of the swarm and (2) moves toward the position where the agent has reached its best location. As a consequence, the collective behavior of the swarm produces that all agents are attracted to the best positions experimented by the swarm. Another example is the ant colony optimization (ACO) which models the biological pheromone trail following behavior of ants. Under this mechanism, each ant senses pheromone concentrations in its local position. Then, it probabilistically selects the path with the highest pheromone concentration. Considering this model, the collective effect in the swarm is to find the best option (shortest path) from a group of alternatives available in a decision-making problem.

There exist several features that clearly appear in most of the metaheuristic and swarm approaches, such as the use of diversification to force the exploration of regions of the search space, rarely visited until now, and the use of intensification or exploitation, to investigate thoroughly some promising regions. Another interesting feature is the use of memory to store the best solutions encountered. For these reasons, metaheuristics and swarm methods quickly became popular amongst researchers to solve from simple to complex optimization problems in different areas.

Most of the problems in science, engineering, economics, and life can be translated as an optimization or a search problem. According to their characteristics, some problems can be simple that can be solved by traditional optimization methods based on mathematical analysis. However, most of the problems of practical importance such as system identification, parameter estimation, energy systems, represent conflicting scenarios so that they are very hard to be solved by using traditional approaches. Under such circumstances, metaheuristic and swarm algorithms have emerged as the best alternative to solve this kind of complex formulations. Therefore, swarm techniques have consolidated as a very active research subject in the last ten years. During this time, various new swarm approaches have been introduced. They have been experimentally examined on a set of artificial benchmark problems and in a large number of practical applications. Although metaheuristic and swarm methods represent one of the most exploited research paradigms in computational intelligence, there are a large number of open challenges in the area of swarm intelligence. They range from premature convergence, inability to maintain population diversity and the combination of swarm paradigms with other algorithmic schemes, toward extending the available techniques to tackle ever more difficult problems.

Numerous books have been published tacking in account any of the most widely known swarm methods, namely ant colony algorithms and particle swarm optimization but attempts to consider the discussion of new alternative approaches are always scarce. Initial swarm schemes maintain in their design several limitations such as premature convergence and inability to maintain population diversity. Recent swarm methods have addressed these difficulties providing in general better results. Many of these novel swarm approaches have also been lately introduced. In general, they propose new models and innovative cooperation models for producing an adequate exploration and exploitation of large search spaces considering a significant number of dimensions. Most of the new metaheuristic swarm present promising results. Nevertheless, they are still in their initial stage. To grow and attain their complete potential, new swarm methods must be applied in a great variety of problems and contexts, so that they do not only perform well in their reported sets of optimization problems, but also in new complex formulations. The only way to accomplish this is by making possible the transmission and presentation of these methods in different technical areas as optimization tools. In general, once a scientific, engineering, or practitioner recognizes a problem as a particular instance of a more generic class, he/she can select one of the different swarm algorithms that guarantee an expected optimization performance. Unfortunately, the set of options are concentrated in algorithms whose popularity and high proliferation are better than the new developments.

The excessive publication of developments based on the simple modification of popular swarm methods presents an important disadvantage: They avoid the opportunity to discover new techniques and procedures which can be useful to solve problems formulated by the academic and industrial communities. In the last years, several promising swarm schemes that consider very interesting concepts and operators have been introduced. However, they seem to have been completely overlooked in the literature, in favor of the idea of modifying, hybridizing, or restructuring popular swarm approaches.

The goal of this book is to present advances that discuss new alternative swarm developments which have proved to be effective in their application to several complex problems. The book considers different new metaheuristic methods and their practical applications. This structure is important to us, because we recognize this methodology as the best way to assist researchers, lecturers, engineers, and practitioners in the solution of their own optimization problems.

This book has been structured so that each chapter can be read independently from the others. Chapter 1 describes the main characteristics and properties of metaheuristic and swarm methods. This chapter analyses the most important concepts of metaheuristic and swarm schemes.

Chapter 2 discusses the performance and main applications of each metaheuristic and swarm method in the literature. The idea is to establish the strength and weaknesses of each traditional scheme from practical perspective.

The first part of the book that involves Chaps. 3, 4, 5, and 6 present recent swarm algorithms their operators and characteristics. In Chap. 3, an interesting swarm optimization algorithm called the Selfish Herd Optimizer (SHO) is presented for solving global optimization problems. SHO is based on the simulation of the widely observed selfish herd behavior manifested by individuals within a herd of animals subjected to some form of predation risk. In SHO, individuals emulate the predatory interactions between groups of prey and predators by two types of search agents: the members of a selfish herd (the prey) and a pack of hungry predators. Depending on their classification as either a prey or a predator, each individual is conducted by a set of unique evolutionary operators inspired by such prey–predator relationship. These unique traits allow SHO to improve the balance between exploration and exploitation without altering the population size. The experimental results show the remarkable performance of our proposed approach against those of the other compared methods, and as such SHO is proven to be an excellent alternative to solve global optimization problems.

Chapter 4 considers a recent swarm algorithm called the Social Spider Optimization (SSO) for solving optimization tasks. The SSO algorithm is based on the simulation of cooperative behavior of social spiders. In the proposed algorithm, individuals emulate a group of spiders which interact with each other based on the biological laws of the cooperative colony. The algorithm considers two different search agents (spiders): males and females. Depending on gender, each individual is conducted by a set of different evolutionary operators which mimic different cooperative behaviors that are typically found in the colony. In order to illustrate the proficiency and robustness of the proposed approach, it is compared to other well-known evolutionary methods. The comparison examines several standard benchmark functions that are commonly considered within the literature of evolutionary algorithms. The outcome shows a high performance of the proposed method for searching a global optimum with several benchmark functions.

In Chap. 5, a swarm algorithm called Locust Search (LS) is presented for solving optimization tasks. The LS algorithm is based on the simulation of the behavior presented in swarms of locusts. In the proposed algorithm, individuals emulate a group of locusts which interact with each other based on the biological laws of the cooperative swarm. The algorithm considers two different behaviors: solitary and social. Depending on the behavior, each individual is conducted by a set of evolutionary operators which mimic the different cooperative behaviors that are typically found in the swarm. In order to illustrate the proficiency and robustness of the proposed approach, it is compared to other well-known evolutionary methods. The comparison examines several standard benchmark functions that are commonly considered within the literature of evolutionary algorithms. The outcome shows a high performance of the proposed method for searching a global optimum with several benchmark functions.

Chapter 6 presents an algorithm for global optimization called the collective animal behavior (CAB). Animal groups, such as schools of fish, flocks of birds, swarms of locusts, and herds of wildebeest, exhibit a variety of behaviors including swarming about a food source, milling around a central location, or migrating over large distances in aligned groups. These collective behaviors are often advantageous to groups, allowing them to increase their harvesting efficiency, to follow better migration routes, to improve their aerodynamic, and to avoid predation. In the presented swarm algorithm, the searcher agents emulate a group of animals which interact with each other based on the biological laws of collective motion. The method has been compared to other well-known optimization algorithms. The results show good performance of the proposed method when searching for a global optimum of several benchmark functions.

The second part of the book which involves Chaps. 7, 8, and 9 presents the use of recent swarm algorithms in different domains. The idea is to show the potential of new swarm alternatives algorithms from a practical perspective.

In Chap. 7, an algorithm for the optimal parameter calibration of fractional fuzzy controllers (FCs) is presented. Fuzzy controllers (FCs) based on integer schemes have demonstrated their performance in an extensive variety of applications. However, several dynamic systems can be more accurately controlled by fractional controllers. Under such conditions, there is currently an increasing interest in generalizing the design of FCs with fractional operators. In the design stage of fractional FCs, the parameter calibration process is transformed into a multidimensional optimization problem where fractional orders as well as controller parameters of the fuzzy system are considered as decision variables. To determine the parameters, the proposed method uses the swarm method called Social Spider Optimization (SSO) which is inspired by the emulation of the collaborative behavior of social spiders. In SSO, solutions imitate a set of spiders which cooperate to each other based on the natural laws of the cooperative colony. Different to the most of existent evolutionary algorithms, it explicitly avoids the concentration of individuals in the best positions, avoiding critical flaws such as the premature convergence to suboptimal solutions and the limited exploration–exploitation balance. Numerical simulations have been conducted on several plants to show the effectiveness of the proposed scheme.

Chapter 8 presents an algorithm for the automatic selection of pixel classes for image segmentation. The presented method combines a swarm method with the definition of a new objective function that appropriately evaluates the segmentation quality with respect to the number of classes. The employed swarm algorithm is the Locust Search (LS) which is based on the behavior of swarms of locusts. Different to the most of existent evolutionary algorithms, it explicitly avoids the concentration of individuals in the best positions, avoiding critical flaws such as the premature convergence to suboptimal solutions and the limited exploration–exploitation balance. Experimental tests over several benchmark functions and images validate the efficiency of the proposed technique with regard to accuracy and robustness.

Chapter 9 presents an algorithm for the automatic detection of circular shapes embedded into cluttered and noisy images without considering conventional Hough transform techniques. The approach is based on a swarm technique known as the collective animal behavior (CAB). In CAB, searcher agents emulate a group of animals which interact with each other based on simple biological laws that are modeled as swarm operators. The approach uses the encoding of three non-collinear points embedded into an edge-only image as candidate circles. Guided by the values of the objective function, the set of encoded candidate circles (charged particles) are evolved using the CAB algorithm so that they can fit into actual circular shapes over the edge-only map of the image. Experimental evidence from several tests on synthetic and natural images which provide a varying range of complexity validates the efficiency of our approach regarding accuracy, speed, and robustness.

Finally, In Chap. 10, the swarm optimization algorithm of Locust Search (LS) is applied to a template-matching scheme. In the approach, the LS method is considered as a search strategy in order to find the pattern that better matches in the original image. According to a series of experiments, LS achieves the best results between estimation accuracy and computational load.

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