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On the performance of artificial bee colony (ABC) algorithm

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Abstract

Artificial bee colony (ABC) algorithm is an optimization algorithm based on a particular intelligent behaviour of honeybee swarms. This work compares the performance of ABC algorithm with that of differential evolution (DE), particle swarm optimization (PSO) and evolutionary algorithm (EA) for multi-dimensional numeric problems. The simulation results show that the performance of ABC algorithm is comparable to those of the mentioned algorithms and can be efficiently employed to solve engineering problems with high dimensionality.

Keywords: Swarm intelligence; Bee colony algorithm; ABC; DE; PSO; EA; Numerical optimization

1. Introduction

Evolutionary algorithms (EA) are generally known as general-purpose optimization algorithms, which are capable of finding near-optimal solutions to the numerical, real-valued test problems for which exact and analytical methods do not produce optimal solutions within a reasonable computation time. One of the evolutionary algorithms which has been introduced recently is differential evolution (DE) algorithm [1]. The DE algorithm has been proposed to overcome the main disadvantage of poor local search ability of genetic algorithm (GA) [2]. The important difference between the GA and the DE algorithm is at the selection operations they employed.

At the selection operation of the GA, the chance of being selected of a solution as a parent depends on the fitness value of that solution. In DE algorithm, all solutions have an equal chance of being selected as parents, i.e. the chance does not depend on their fitness values. After a new solution is produced by using a self-adjusting mutation operation and a crossover operation, the new solution competes with its parent for the next generation and the better one wins the competition. In other words, a greedy scheme is applied to select one of them for the next generation. The use of a mutation operation, which has the self-adaptability feature, a crossover operation and a greedy process for the selection, makes DE a fast converging evolutionary algorithm. Besides its simplicity and flexibility, DE also does not face any Hamming Cliff problem like the binary GA [3,4]. Therefore, DE algorithm has received significant interest from researchers studying in different research areas and has been applied to several real-world problems [5–8].

Swarm intelligence has become a research interest to many research scientists of related fields in recent years. The swarm intelligence is defined as "...any attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insect colonies and other animal societies..." by Bonabeau et al. [9]. Bonabeau et al. focused their viewpoint on social insects alone, such as termites, bees, wasps as well as different ant species. However, the term swarm is used in a general manner to refer to any restrained collection of interacting agents or individuals. The classical example of a swarm is bees swarming around their hive; nevertheless the metaphor can easily be extended to other systems with a similar architecture. For instance, an ant colony can be thought of as a swarm whose individual agents are ants; a flock of birds is a swarm of birds; an immune system [10] is a swarm of cells as well as a crowd is a swarm of people [11].

Particle swarm optimization (PSO) algorithm, which has become quite popular recently, models the social behaviour of bird flocking or fish schooling [12]. PSO is a population-based stochastic optimization technique and well adapted to the optimization of nonlinear functions in multi-dimensional

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space. PSO consists of a swarm of particles moving in a search space of possible solutions for a problem. Every particle has a position vector representing a candidate solution to the problem and a velocity vector. Moreover, each particle contains a small memory that stores its own best position seen so far and a global best position obtained through communication with its neighbour particles.

A few models have been developed to model the intelligent behaviours of honeybee swarms and applied for solving combinatorial type problems [13–20]. There is only one numerical optimization algorithm in the literature based on intelligent behaviour of honeybee swarms [21]. Yang developed a virtual bee algorithm (VBA) [21] to solve the numerical optimization problems. VBA has been introduced to optimize only the functions with two parameters. In VBA, a swarm of virtual bees are generated and started to move randomly in the phase space. These bees interact when they find some target nectar corresponding to the encoded values of the function. The solution for the optimization problem can be obtained from the intensity of bee interactions. For optimizing multivariable numerical functions, Karaboga has described a bee swarm algorithm called artificial bee colony (ABC) algorithm [22], which is different from the virtual bee algorithm, and Basturk and Karaboga compared the performance of ABC algorithm with the performance of GA in [23].

This work compares the performance of ABC algorithm with that of DE and PSO algorithms, and EA for a set of well-known test functions. Also, the performance of ABC is analysed under the change of control parameter values. In Section 2, the behaviour of real honeybees is described and then the artificial bee colony algorithm is introduced in Section 3. In Section 4, the experimental study is described and finally, the simulation results obtained are presented and discussed in Section 5.

2. Behaviour of real bees

The minimal model of forage selection that lead to the emergence of collective intelligence of honey bee swarms consists of three essential components: food sources, employed foragers and unemployed foragers, and defines two leading modes of the behaviour: recruitment to a nectar source and abandonment of a source [24].

(i) Food sources: the value of a food source depends on many factors, such as its proximity to the nest, richness or concentration of energy and the ease of extracting this energy. For the simplicity, the ‘‘profitability’’ of a food source can be represented with a single quantity [25].
(ii) Employed foragers: they are associated with a particular food source, which they are currently exploiting or are ‘‘employed’’ at. They carry with them information about this particular source, its distance and direction from the nest and the profitability of the source and share this information with a certain probability.
(iii) Unemployed foragers: they are looking for a food source to exploit. There are two types of unemployed foragers—scouts searching the environment surrounding the nest for new food sources and onlookers waiting in the nest and finding a food source through the information shared by employed foragers. The mean number of scouts averaged over conditions is about 5–10% [25].

The exchange of information among bees is the most important occurrence in the formation of collective knowledge. While examining the entire hive, it is possible to distinguish some parts that commonly exist in all hives. The most important part of the hive with respect to exchanging information is the dancing area. Communication among bees related to the quality of food sources occurs in the dancing area. The related dance is called waggle dance. Since information about all the current rich sources is available to an onlooker on the dance floor, she probably could watch numerous dances and choose to employ herself at the most profitable source. There is a greater probability of onlookers choosing more profitable sources since more information is circulating about the more profitable sources. Employed foragers share their information with a probability, which is proportional to the profitability of the food source, and the sharing of this information through waggle dancing is longer in duration. Hence, the recruitment is proportional to profitability of a food source [15].

In order to understand the basic behaviour characteristics of foragers better, let us examine the Fig. 1. Assume that there are two discovered food sources: A and B. At the very beginning, a potential forager will start as unemployed forager. That bee will have no knowledge about the food sources around the nest.

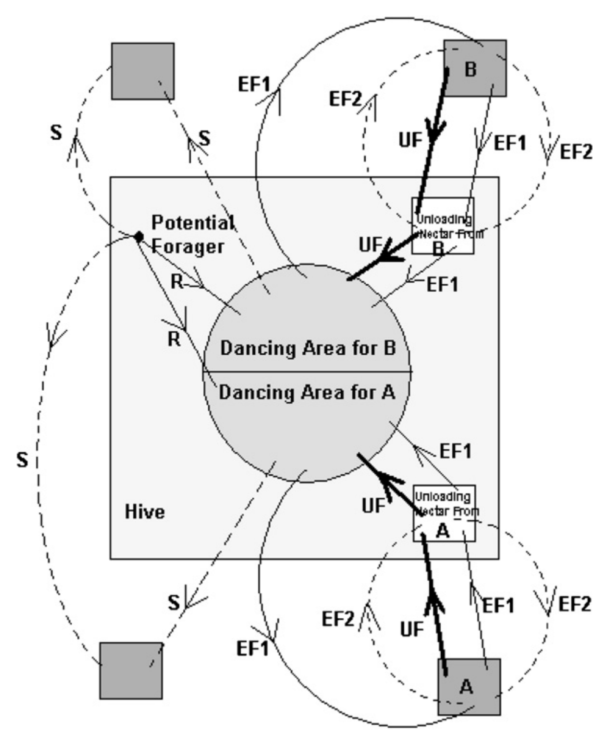

Fig. 1. Behaviour of honeybee foraging for nectar.