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Enhanced compact artificial bee colony

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ABSTRACT

Challenges in many real-world optimization problems arise from limited hardware availability, particularly when the optimization must be performed on a device whose hardware is highly restricted due to cost or space. This paper proposes a new algorithm, namely Enhanced compact Artificial Bee Colony (EcABC) to address this class of optimization problems. The algorithm benefits from the search logic of the Artificial Bee Colony (ABC) algorithm, and similar to other compact algorithms, it does not store the actual population of tentative solutions. Instead, EcABC employs a novel probabilistic representation of the population that is introduced in this paper. The proposed algorithm has been tested on a set of benchmark functions from the CEC2013 benchmark suite, and compared against a number of algorithms including modern compact algorithms, recent population-based ABC variants and some advanced meta-heuristics. Numerical results demonstrate that EcABC significantly outperforms other state of the art compact algorithms. In addition, simulations also indicate that the proposed algorithm shows a comparative performance when compared against its population-based versions.

1. Introduction

The technology being used in the industry is progressively developing affecting the applied optimization problems to be more and more complicated. One of the areas of concern is bound constrained optimization problems. The existing derivative-based optimization methods are not effective to solve hard optimization problems in reasonable time, especially when the value of the objective function can either be obtained by direct measurement or through simulation. As an alternative, derivative-free methods can be designed to solve a wide range of practical optimization problems in areas ranging from science to engineering [46].

The efficiency and effectiveness of the derivative-free methods depend on strong global convergence and the ability to make significant progresses with few function evaluations. These methods can roughly be subsumed under just two broad categories, namely population based and single solution based methods. The population based methods, in turn can be divided into Evolutionary Computation (EC) and Swarm Intelligence (SI) approaches. A recent comprehensive survey on these methods can be found in [8].

The computational power of the SI optimization methods is inspired by collective behavior of social animals. It has recently encouraged a great interest among researchers leading to many significant studies each focusing on a different branch of this methodology [49,53]. A typical method in this family consists of a population of several agents each interacts locally with other ones and with its environment resulting in a globally self-organized behavior.

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There have been several classes of optimization algorithms proposed in the SI framework including, Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) [32,44], Artificial Bee Colony (ABC) [2,31], Artificial Immune Systems (AIS), Glowworm Swarm Optimization (GSO), Intelligent Water Drops (IWD), Gravitational Search Algorithm (GSA), Charged System Search (CSS), Stochastic Diffusion Search (SDS), River Formation Dynamics (RFD), and Multi-Swarm Optimization (MSO).

Among these approaches, ABC has gained recent prominence. The algorithm was inspired by the intelligent collective foraging behavior of honeybee swarm [29]. The characteristics of ABC include, possessing few control parameters, simple to implement and being competitive with other population-based algorithms [30]. These features have stimulated significant contributions in this area, particularly to address bound constraint optimization problems [6,11].

Although these methods can efficiently be applied to approximate a solution for a wide variety of optimization problems, their applications typically rely on the storage of a number of trial solutions. On the other hand, in spite of the progressive advances being made in the development of contemporary computational devices, some real world applications still require the solution of a challenging optimization problem on a device where the full components of a modern computer cannot be used. As pointed out by Neri et al. [42] this situation can either be due to cost and space limitations, or the need for real-time optimization, or even might due to fault-tolerance requirements. For instance, a relatively simple hardware has to be used on space shuttles in order to reduce fault risks. In addition, the smooth functioning of small mobile robotic systems such as a vacuum cleaner robot depends on the existence of a computational unit inside these machines where real-time optimization has to be performed on the limited hardware of a microcontroller [28,43]. Additionally, some very interesting case studies have been described by Mininno, et al. [37,38] which are expressive of the need for memory-saving algorithms.

In order to address this requirement, a class of algorithms with regulated memory requirements has been designed. Some embodiments of these algorithms belong to the class of Estimation of Distribution Algorithms (EDAs) [33]. One advantage of applying these algorithms is to make use of an estimated virtual population in contrast to store an entire population of individuals, hence reducing the need for data storage.

The objective of this paper is to propose a new optimization algorithm called Enhanced compact Artificial Bee Colony (EcABC). The EcABC is formulated based on the EDA framework and the ABC algorithm, inheriting the memory-saving capability of the EDA family and efficiency of ABC algorithm. The EcABC also modifies the original ABC method to alleviate suffering from exploitation problem.

The remainder of this paper is organized as follows. A brief review of related works is presented in the next section. This is followed by a review on the recent advances on the ABC algorithms. The EcABC algorithm is then introduced in the third section. Following that, the experimental results on the benchmark optimization problems are presented and analyzed. Finally, the last section contains the summary and some concluding remarks.

2. Related works

In recent years investigations on memory-saving algorithms have led to development of compact optimization algorithms [40]. The class of compact algorithms belongs to the EDA family. The methods in this class resemble the population-based methods as they use very similar search operators. However, the compact algorithms use different approach to exploit the population which is quite a contrast to what their counterparts usually do. These algorithms do not save an explicit representation of the whole population. Instead, they use a probability distribution that is iteratively biased toward an optimal solution.

The first work in the area was the compact Generic Algorithm (cGA) which showed comparable performance against standard GA [22]. The convergence properties of this algorithm was studied in [45]. Under assumption that estimation of good probability distribution is equivalent to linkage learning, this algorithm was further improved to introduce the extended compact Genetic Algorithm (ecGA) [23]. These studies have led to develop some variants of the cGA [3,13,27], and the real-encoded cGA (rcGA) [37].

The compact Differential Evolution (cDE) algorithm has been introduced in [38] where it has been verified that this algorithm outperforms rcGA, and is also competitive with its corresponding population based versions. This algorithm utilize a one-to-one spawning survivor selection mechanism which is naturally inherited from the DE algorithm, and gains advantage from randomization feature of the probabilistic model on offspring generation.

A variant of cDE, called Memetic compact Differential Evolution (McDE), was presented in [41]. The McDE employs a stochastic local search algorithm to iteratively modify search direction. An unconventional mimetic approach was also introduced in [39] to develop the Disturbed Exploitation compact Differential Evolution (DEcDE). In addition, the effect of opposition-based learning mechanism [51] on the cDE has been studied in [25].

In [42], the compact encoding design of PSO, namely the compact Particle Swarm Optimization (cPSO) algorithm has been introduced. As the name suggests this algorithm benefits from the search mechanism of PSO. The sampling strategy in cPSO shares the same feature as in rcGA. However, it has been shown that cPSO performs competitively when comparing against other compact methods [42].

Recently, a compact version of ABC algorithm has also been suggested by Dao et al. [9] called compact ABC (cABC). The cABC has been developed aiming to improve the original ABC algorithm [29]. However, this algorithm has not been tested on modern test problems nor it has been compared against other compact algorithms.