Applied Mathematics and Computation 219 (2012) 3575–3589

Contents lists available at SciVerse ScienceDirect

Applied Mathematics and Computation

journal homepage: www.elsevier.com/locate/amc

Simulated annealing based artificial bee colony algorithm for global numerical optimization

Shi-Ming Chen *, Ali Sarosh, Yun-Feng Dong

School of Astronautics, Beijing University of Aeronautics and Astronautics, Beijing 100191, PR China

ARTICLE INFO

Keywords:
Artificial bee colony
Simulated annealing algorithm
Global best guided ABC
Global numerical optimization
Swarm intelligence
Optimization

ABSTRACT

Artificial bee colony (ABC) algorithm is a global optimization algorithm, which has been shown to be competitive with some conventional swarm algorithm, such as genetic algorithm (GA) and particle swarm optimization (PSO). However, there is still an insufficiency in ABC algorithm, in that it has poor convergence rate in some situations. Inspired by simulated annealing algorithm, a simulated annealing based ABC algorithm (SAABC) is proposed. Simulated annealing algorithm is introduced into employed bees search process to improve the exploitation of the algorithm. The experimental results are tested on a set of numerical benchmark functions with different dimensions. That show that SAABC algorithm can outperform ABC and global best guided ABC algorithms in most of the experiments.

© 2012 Elsevier Inc. All rights reserved.

1. Introduction

Artificial bee colony (ABC) algorithm was proposed by Karaboga in [1], it is based on swam intelligence and is applied to global optimization problems [1]. It is inspired by the intelligent foraging behavior of honey bee swarm. Compared with genetic algorithm (GA) and particle swarm optimization (PSO) [2,3], ABC has lower computation complexity, easier programming and outstanding performance. This has raised great interest amongst researchers in recent years. The ABC algorithm has been extended for optimization of multitude of design problem including constrained optimization problems in [4], training of neural network [5], designing digital IIR filters [6], solution of TSP problems [1], processing images, recognizing patterns [7–9], structural optimization [10–13] and data clustering [14–19]. Akay and Karaboga [20] gave a modified version of the ABC algorithm to solve optimization problem for real parameters. Xu et al. [21] discussed an improved ABC optimization algorithm based on chaos theory for solving the path planning problem of Uninhabited Combat Air Vehicle (UCAV). Pan et al. [22] proposed a discrete artificial bee colony (DABC) algorithm to solve the lot-streaming flow shop scheduling problem. Bernardino et al. [23] developed an efficient traffic loading algorithm using ABC to find the routing of Weighted Ring Arc-Loading Problem (WRALP). Yeh and Hsieh [24] proposed a penalty guided ABC to solve the reliability redundancy allocation problem.

Although ABC has been successfully applied in many fields, however according to [25], the basic ABC algorithm is good at exploration but poor at exploitation. Exploration and exploitation are necessary for the population-based optimization algorithms [25,26]. While exploration process is related to the independent search for an optimal solution, exploitation uses existing knowledge to find better solutions. In practice, the exploration and exploitation contradict each other, and in order to achieve good optimization performance, the two abilities should be well balanced.

* Corresponding author. Address: 37 Xueyuan Road, New Main Building, Office B-324, Haidian District, Beijing 100191, PR China.
E-mail addresses: csm7531@sa.buaa.edu.cn (S.-M. Chen), alisarosh@sa.buaa.edu.cn (A. Sarosh), sinosat@buaa.edu.cn (Y.-F. Dong).

0096-3003/$ - see front matter © 2012 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.amc.2012.09.052

Like most population-based algorithms, ABC takes a long time because of its stochastic nature. To improve the convergence characteristics and to prevent the ABC from getting stuck in local solutions, chaos theory [27,21,16] was introduced into the algorithm to replace the random number. The results showed that the proposed method increased the solution quality and improved the global searching capability. Some local search techniques, such as Rosenbrock method (RM) and Nelder-Mead simplex search method (NMSS), were introduced into the ABC algorithm, by Kang et al. [28,10]. Comparison results showed that the proposed methods performed better than basic ABC algorithm. The best-so-far ABC algorithm has been presented by Banharnsakun et al. [26], it provides solution update of the onlooker bees. There are three changes in this best-so-far ABC. Firstly, the best feasible solutions found so far, are shared globally among the entire population. Secondly, in each iteration, the radius of the search for new candidates uses a larger radius than employed earlier in the search process and subsequently reduces the radius as the process comes closer to convergence. Finally, a robust calculation to determine and compare the quality of alternative solutions was used. The results demonstrated that the proposed method produced higher quality solutions with faster convergence. In order to improve the exploitation, the global-best-solution guided ABC (GABC) was proposed by Zhu and Kwong [25]. In GABC, the global best solution information was incorporated into the solution search equation. The approach improved the convergence rate and hence the capability of convergence up to a global optimum. The experimental results from these improved ABC algorithms showed that it could successfully solve numerical optimization problems. However, in some cases the convergence speed could be an issue. In order to overcome this shortcoming and improve the performance of ABC algorithm, this paper introduces a simulated annealing based ABC algorithm.

Simulated annealing (SA) algorithm is a general-purpose stochastic optimization method that has proven to be quite effective in finding global optima for many problems. Recent interest began with the works of Kirkpatrick et al. [29], and Cerny [30]. The simulated annealing algorithm was initially proposed by Kirkpatrick et al. [29], who drew an analogy between the cooling of a fluid and the optimization of a complex system. Simulated annealing is based on the theory of Markov chains, it accepts and rejects randomly generated 'moves' on the basis of a probability related to an 'annealing' temperature [31]. It can accept moves which change the value of an objective function in the direction opposite to that of the desired long-term trend. Thus, for a global minimization problem, a move that increase the value of the objective function may be accepted as part of the full series of moves for which the general trend is to decrease the value of the objective function. In this way, simulated annealing is able to explore the full solution space and can escape from the local optima. Simulated annealing has proven to be a practical method for solving combinatorially large optimization problems. Press [32] report that simulated annealing can obtain solutions to combinatorial optimization problems within specified 'distance' of the global optimum.

ABC is a swarm intelligence algorithm, while SA focus on the evolution process of individuals. If improving the individual's evolution process of ABC algorithm, the convergence speed will be increased and ABC algorithm will get better result. So a new algorithm combined two algorithms is proposed.

In this paper, the employed bees searching process is modified by SA algorithm so as to increase the convergence rate. Hereinafter the SA based ABC algorithm is referred to SAABC algorithm. The design of computational experiment for testing of SAABC heuristic algorithm is carried out in accordance with guidelines provided by Barr et al. [33]. Experimental results tested on optimization of numerical functions show that SAABC is superior to ABC and GABC algorithms in most of the cases. Details of the work are presented in subsequent sections of this paper. Section 2 summarizes basic ABC, SA and SAABC algorithms. Section 3 describes the test functions and parameters. In Section 4, the optimal parameters of SAABC are chose and numerical test result obtained for ABC, GABC and SAABC algorithms are compared. Conclusions are made based on the results of numerical comparisons of the aforementioned methods.

2. Optimization theory and methods

2.1. Basic artificial bee colony algorithm

In a natural bee swarm, there are generally three kinds of honey bees that search food. These include the employed bees, the onlookers, and the scouts. Employed bees are responsible for exploiting the nectar sources, they explore the site beforehand and give information to the onlooker bees in the hive about the quality of the food at the source sites which they are exploiting. Onlooker bees wait in the hive and decide on a food source to exploit based on the information shared by the employed bees. Scouts randomly search the environment in order to find a new food source, either depending on an internal motivation or based on possible external clues [20].

In ABC algorithm [19], each employed bee uses the currently associated food source to determine a new neighboring source, based on the nectar amount at the new source. Eq. (1) shows the method to determine the nectar amount of this new food source.

$$v_{ij} = x_{ij} + \theta_{ij}(x_{ij} - x_{kj}), \tag{1}$$

where $i,j \in \{1,2,\ldots,D\}$ are randomly chosen indexes and $k \in \{1,2,\ldots,SN\}$. D is the variables dimensions, and SN is the number of food sources which is equal to the number of employed bees. Although k is determined randomly, it has to be different from i. The θ_{ij} is a randomly produced number between $[-1,1]$.

Download English Version:

https://daneshyari.com/en/article/4629335

Download Persian Version:

https://daneshyari.com/article/4629335

Daneshyari.com