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Research Article

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Artificial Bee Colony Algorithm Using Weighted Average Information of Swarm

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Abstract: Artificial bee colony (ABC) algorithm is a new computational method for tackling optimization functions. However, it is easily trapped into the local optima when solving high-dimension functions. A modified artificial bee colony algorithm using weighted average information of swarm is presented to overcome this shortcoming. In our method, the new food source is generated by using weighted average information of swarm. In the simulations by using benchmark test functions, experiment data shows that this new algorithm has rapidly convergent in optima search.

Keywords: Artificial bee colony; Swarm intelligence; Evolutionary computation

1. Introduction

Meta-heuristic optimization techniques have become very popular over the last two decades. Surprisingly, some of them such as Ant Colony Optimization (ACO) [1], Particle Swarm Optimization (PSO)[2], and Artificial Bee Colony (ABC)[3] algorithm are fairly well-known among not only computer scientists but also scientists from different fields. These algorithms simulate the collective behavior of groups of simple agents like colonies of ants, flocks of birds, swarm of bees, and so on. Inspired by the foraging behaviour and waggle dance behaviour of honeybee swarm, the artificial bee colony (ABC) algorithm was first proposed in 2005. Specifically, through imitating the behavior of searching for food source of honeybee colony, the ABC algorithm performs optimization search processes. When compared with some classical evolutionary algorithms such as genetic algorithm (GA), particle swarm optimization, and differential evolution (DE), the ABC algorithm exhibits a very good performance [4-6]. What is more, it also owns some merits of simple structure, easy implementation and fewer control parameters. Thus, more and more researchers start to focus on investigating the improvement and application of ABC algorithms from different aspects. Thereafter, the ABC algorithm has been widely and successfully used in many fields [7-13].

However, the ABC algorithm is good at exploration but poor at exploitation, it is easily trapped in local optima when solving some complex multimodal optimization problems. In order to overcome the shortage, many enhanced versions of ABC have been developed. For instance, inspired by particle swarm optimization, Zhu and Kwong [14] introduced a gbest-guided artificial bee colony, named GABC. Motivated by the mutation strategy of differential evolution, Gao and Liu [15] proposed an improved solution search equation, which is employed to balance the exploration ability of the original solution search equation. In view of only changing one parameter in basic ABC, which results in a slow convergence rate, Akay and Karaboga [16] first introduced a control parameter, i.e., modification rate (MR), which is used to control the frequency of perturbation. Meanwhile, an adaptive scaling factor is also designed. Then the convergence rate is effectively speeded up. Wang et al. [17] proposed the MEABC algorithm to improve the local and global search capability of the basic ABC algorithm.

To further enhance the convergence performance of the traditional ABC algorithm, in this paper, we proposed a new algorithm, named ABCUWAIS, in which the new food source is generated by using weighted average information of swarm. Then a new probability scheme is proposed for choosing a neighbor. The proposed ABCUWAIS algorithm is tested on a number of benchmark functions and compared with its several variants. The experimental results indicate that the proposed approach has better convergence performance.

The rest of the paper is organized as follows. Section 2 describes the traditional artificial bee colony algorithm. In Section 3, the artificial bee colony algorithm using weighted average information of swarm is proposed. In Section 4, a comprehensive experimental study is carried out, and the related experimental results are provided and discussed. Finally, some conclusions are drawn in Section 5.

2. Traditional Artificial Bee Colony Algorithm

Through simulating the intelligent foraging behaviour of honeybee colony, Karaboga first proposed the well-known meta-heuristic optimization algorithm, i.e., the artificial bee colony (ABC) algorithm. In ABC algorithm, the honey bee swarm is divided into three groups, i.e., employed bees, onlooker bees and scout bees. Employed bees are responsible for exploiting the food sources and sharing the information about these food sources. Onlooker bees wait in the hive and take the food source information from employed bees to make a decision on further exploiting the food source. Scout bees randomly search for the environment to find a new food source.

In ABC algorithm, the number of food sources is equal to number of employed bees and also number of employed bees equals to number of onlooker bees. All the employed bees are scout bees at the starting of the algorithm and a food source position is produced for each scout bee using Eq. (1):

$$x_i^j = x_{\min}^j + rand\,(x_{\max}^j - x_{\min}^j) \tag{1}$$

where $i = 1, 2, \ldots, SN$, $j = 1, 2, \ldots, D$, x_i^j is the jth dimension of ith food source which will be assigned to ith employed bee, $x_{\min}^j$ and $x_{\max}^j$ are the lower and upper bounds of the jth dimension, respectively. $rand$ is a random number between $[0,1]$, SN is the number of food sources and D is the dimensionality of the problem or function optimized.

After producing a food source position for each scout bee, all the scout bees become employed bee. The qualities of the food sources of the employed bees are measured by using Eq. (2):

$$fit_i = \begin{cases} \dfrac{1}{1+f_i}, & f_i \geq 0 \\ 1+|f_i|, & f_i < 0 \end{cases} \tag{2}$$

where fit_i is the fitness value of the ith food source and f_i is the objective function value specific for the optimization problem.

The employed bees search around the self-food sources for new food sources. A new food source position around the food source of employed bee is obtained as follows:

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{3}$$

where $j \in \{1, 2, \ldots, D\}$ and $k \in \{1, 2, \ldots, SN\}$ are randomly chosen indexes; k is different from i; φ_{ij} is a random real number in range of $[-1,1]$.

The fitness of the candidate food source v_i is obtained by using Eq. (2) and if the fitness of v_i is equal to or better than that of x_i, v_i will replace x_i and become a new member of the population. Otherwise, x_i is retained.

After the employed bees return to the hive, the employed bees share self-food source positions with the onlooker bees. An onlooker bee selects an employed bee and memorizes its food source position in order to improve its food source by using roulette-wheel selection mechanism given as follows:

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{4}$$

After the selection, the onlooker bee selects her food source x_i, she produces a modification on x_i by Eq. (3). If the modified food source has a better or equal nectar amount than x_i, the modified food source will replace x_i and become a new member of the population.

If a food source cannot be improved for a predetermined number of local trials, the food source will be abandoned, then the employed bee associated with that food source becomes a scout bee. Then, the scout bee finds a new food source by Eq. (1). After the scout bee finds a new source, she becomes an employed bee again.

3. Artificial Bee Colony Algorithm Using Weighted Average Information of Swarm

According to the Eq. (3), it can be found that the ith employed bee purely randomly chooses a neighbor to perform a search, which may in part result in the shortcoming of slow convergence rate. In order to achieve good optimization performance, we proposed an improved artificial bee colony algorithm using weighted average information of swarm, named as ABCUWAIS algorithm. In our method, the new food source is generated as follows:

$$v_{ij} = s_1 x_{rj} + (1-s_1)x_{vj} + \varphi_{ij}\left[s_1(x_{rj} - x_{kj}) + (1-s_1)(x_{vj} - x_{kj})\right] \tag{5}$$

$$s_1 = \begin{cases} 0, & rand1 < 0.5 \\ 1, & otherwise \end{cases}$$

$$x_{vj} = \sum_{i=1}^{SN}\left(P_i \cdot x_{ij}\right), j = 1, 2, \ldots, D$$

where x_r is the solution which is randomly selected from the population, r and k are mutually exclusive integers randomly chosen from $\{1, 2, \ldots, SN\}$, and both of them are different from the base index i, x_v is the weighted average information of swarm.

The main process of ABCUWAIS algorithm is given as follows:

1: Set up the related parameters,i.e., SN and the maximum number of functions evaluations $Max.FE$

2: Initialize the population of SN individuals, and evaluate the population

3: While ($FE < Max.FE$)

4: Generate a new solution v_i for employed bees according to the Eq. (5) and evaluate them

5: Apply a greedy selection process between v_i and x_i to select the better one

6: Calculate the probability values P_i for the solutions x_i by Eq. (4)

7: Generate a new solution v_i for onlooker bees according to the Eq. (5) and evaluate them

8: Apply a greedy selection process between v_i and x_i to select the better one

9: Determine the abandoned solution for the scout, if exist, and replace it with a new randomly produce solution x_i by Eq. (1)

10: Record the best solution achieved so far

11: End while

4. Experimental study and comparisons

Benchmark functions and parameter settings

Table 1：Benchmark functions used in experiments

Function	Search Space	Opt.
$f_1(x)=\sum_{i=1}^{D} x_i^2$	[-100,100]	0
$f_2(x)=\sum_{i=1}^{D}\lvert x_i\rvert+\prod_{i=1}^{D}\lvert x_i\rvert$	[-10,10]	0
$f_3(x)=\max_i\{\lvert x_i\rvert, 1\le i\le D\}$	[-100,100]	0
$f_4(x)=\sum_{i=1}^{D}\left(\lfloor x_i+0.5\rfloor\right)^2$	[-100,100]	0
$f_5(x)=\sum_{i=1}^{D-1}[100(x_{i+1}-x_i^2)^2+(1-x_i)^2]$	[-10,10]	0
$f_6(x)=\sum_{i=1}^{D} i x_i^4+\text{random}[0,1)$	[-1.28,1.28]	0
$f_7(x)=\sum_{i=1}^{D}(x_i^2-10\cos(2\pi x_i)+10)$	[-5.12,5.12]	0
$f_8(x)=\frac{1}{4000}\sum_{i=1}^{D} x_i^2-\prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}})+1$	[-600,600]	0
$f_9(x)=20+e-20\exp\{-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\}-\exp\{\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\}$	[-32,32]	0
$f_{10}(x)=0.5+\frac{\sin^2\left(\sqrt{\sum_{i=1}^{D} x_i^2}\right)-0.5}{\left(1+0.001\sum_{i=1}^{D} x_i^2\right)^2}$	[-100,100]	0

In order to investigate the effectiveness of the proposed ABCUWAIS algorithm, ten benchmark functions with which have been widely used in many research works are employed in this work. The definition of each function is presented in Table 1, where information of its mathematical formula, search space and optimal solution is included. The ten benchmark functions provided in Table 1.

Experimental results

The comparisons among ABC algorithm, GABC algorithm [14], ABCbest1 algorithm [18], ABCbest2 algorithm [18], MABC algorithm [15] and ABCUWAIS algorithm are conducted on ten benchmark functions. In all simulations, the population size is 40 (i.e.,), limit is , the number of maximum function evaluations is set to 150000. In the experimental study, each function is optimized over 30 independent runs by each algorithm. The mean and the standard deviation values achieved by each algorithm are summarized in Table 2.

From the Table 2 results, it can be seen that that the compared methods have most reliably found the minimum of the function and, ABC algorithm has the best performance for the function. For the rest of the functions, ABCUWAIS algorithm performs much better in most cases than these ABC variants. it can be concluded ABCUWAIS algorithm can avoid falling into local optimum when solving the complex numerical function problems.

Table 2: Result comparisons of ABCS on 30-dimensional basic functions

Fun	Metric	ABC	GABC	ABCbest1	ABCbest2	MABC	ABCUWAIS
f_1	Mean	4.93E-16	4.62E-16	3.11E-47	5.96E-35	9.43E-32	3.72E-64
	Std	7.98E-17	7.12E-17	3.44E-47	3.61E-35	6.67E-32	2.16E-64
f_2	Mean	1.31E-15	1.35E-15	2.10E-25	1.36E-18	2.40E-17	7.39E-42
	Std	1.54E-16	1.36E-16	9.08E-26	4.27E-19	9.02E-18	1.57E-42
f_3	Mean	8.37E-01	2.18E-01	2.18E+00	3.55E+00	1.02E+01	1.91E-01
	Std	4.72E-01	4.01E-02	3.27E-01	4.79E-01	1.49E+00	3.22E-02
f_4	Mean	0	0	0	0	0	0
	Std	0	0	0	0	0	0

f_5	Mean	4.32E-02	3.21E-01	1.49E+01	5.45E+00	6.11E-01	5.49E-01
	Std	4.51E-02	8.21E-01	2.87E+01	8.40E+00	4.55E-01	4.62E-01
f_6	Mean	4.85E-02	2.03E-02	2.06E-02	2.53E-02	3.71E-02	1.95E-02
	Std	1.29E-02	5.74E-03	4.75E-03	4.67E-03	8.53E-03	4.32E-03
f_7	Mean	0	0	0	0	0	0
	Std	0	0	0	0	0	0
f_8	Mean	1.78E-07	3.70E-17	0	1.81E-08	0	0
	Std	8.89E-07	5.32E-17	0	6.29E-08	0	0
f_9	Mean	3.55E-14	3.20E-14	3.01E-14	3.07E-14	4.13E-14	3.27E-14
	Std	3.62E-15	3.36E-15	2.91E-15	3.43E-15	2.17E-15	4.71E-15
f_{10}	Mean	3.18E-01	2.66E-01	2.39E-01	2.81E-01	2.95E-01	2.36E-01
	Std	5.19E-02	4.39E-02	6.13E-02	3.92E-02	3.17E-02	3.02E-02

5. Conclusion

In this paper, an improved ABC algorithm called ABCUWAIS algorithm has been proposed for global optimization of numerical function problems. In ABCUWAIS algorithm, the new food source is generated by using weighted average information of swarm on the employed bees phase and scout bees phase, respectively, which is used to further balance the exploitation and exploration.

The effectiveness and efficiency of the proposed algorithm is examined on benchmark functions with different characteristics. The experimental results show that the proposed method is efficient and effective in terms of the solution accuracy, stability and robustness. The future works will focus on the application of the proposed method.

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