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An Enhanced Hybridized Artificial Bee Colony Algorithm for Optimization Problems

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Abstract. Artificial bee colony (ABC) algorithm is a popular swarm intelligence based algorithm and there still exist some problems it cannot solve very well. This paper presents an Enhanced Hybridized Artificial Bee Colony (EHABC) algorithm for optimization problems. The incentive mechanism of EHABC includes enhancing the convergence speed with the information of the global best solution in the onlooker bee phase and enhancing the information exchange between bees by introducing the mutation operator of Genetic Algorithm (GA) to ABC in the mutation bee phase. In addition, to enhance the accuracy performance of ABC, when producing the initial population, the opposition-based learning method is employed. Experiments are conducted on a set of 6 benchmark functions. The results demonstrate good performance of the proposed approach in solving complex numerical optimization problems over other four ABC variants.

Keywords: artificial bee colony algorithm, genetic algorithm, population initialization, search equation

1. Introduction

Recently, many heuristic algorithms have been proposed, such as particle swarm optimization algorithm (PSO) [1], differential evolution algorithm (DE) [2] and artificial bee colony algorithm (ABC) [3]. ABC proposed by Karaboga is one of the most popular heuristic algorithms, which is based on the intelligent foraging behaviour of honey bee swarm. For the reason that it is simple and easy to implement, the ABC algorithm has attracted a lot of scholars' attention. Benchmark functions experiment has shown that ABC is competitive over GA [4], DE and PSO algorithm.

However, like other heuristic algorithms, ABC also has some drawbacks in some cases. For example, the solution search equation of ABC is good at exploration but not good at exploitation, which results in the poor convergence [5]. To improve ABC's performance, plenty of variant ABC algorithms have been proposed. Search equation is one of the active research trends. Some researchers integrated ABC with several concepts, which were related to evolutionary optimization algorithms. Inspired by PSO, Gbest-guided ABC algorithm by incorporating the information of global best (gbest) solution into the solution search equation was proposed by Zhu and Kwong [5]. Tuba et al. proposed GABC which integrated ABC with self-adaptive guidance adjusted for engineering optimization problems in [6]. Inspired by GA, TRAN Dang Cong et al. proposed a novel hybrid data clustering algorithm based on artificial bee colony algorithm by incorporating the solution search equation of GABC and proposing a mutation operation to improve the algorithm both in exploitation capability and exploration capability [7].

The researchers of this paper noted that the information of global best solution could be used to improve the exploitation and the crossover operation of GA could be combined with ABC to enhance the exploration

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and exploitation abilities of ABC. Hence, an enhanced hybridized ABC algorithm for optimization problems was proposed in this paper. And the efficiency of EHABC was tested by 6 benchmark functions.

The rest of the paper is organized as follows. In Section 2, the original ABC Algorithm is briefly described. The modifications to the original ABC algorithm are introduced in Section 3. In Section 4, experiments are conducted and the results are discussed. Finally, conclusion is made in Section 5.

2. Artificial Bee Colony Algorithm

In ABC algorithm, the colony of the artificial bees contains three categories: employed bees, onlookers and scouts. A possible solution to the optimization problem is represented by the position of a food source, and the nectar amount of each food source corresponds to the quality (fitness) of the associated solution. The number of food sources equals to the number of the employed bees [3].

At the initialization step, ABC generates a randomly distributed initial population P of SN food source positions (solutions), where SN denotes the number of employed bees or onlooker bees and equals to half of the colony size. Each initial solution $X_i = \{x_{i,1}, x_{i,2}, ..., x_{i,D}\}$ is produced randomly within the range of the boundaries of the parameters, where $i = 1, 2, ..., SN$ and D is the dimension of optimization problems.

After the initialization, the population of the food sources is subjected to repeated cycles of the search processes of the employed bees, onlooker bees and scout bees. Each employed bee and onlooker bee is assigned a task of searching a new food source. To produce a candidate food position V_i from the old position X_i in memory, ABC uses Eq. 2.1 as follows:

$$v_{i,j} = x_{i,j} + \phi_{i,j}(x_{i,j} - x_{k,j}) \tag{2.1}$$

where $k \in \{1, 2, ..., SN\}$ and $j \in \{1, 2, ..., D\}$ are randomly chosen indexes; k has to be different from i, and $\phi_{i,j}$ is a number randomly selected in the range $[-1, 1]$. An onlooker bee selects a food source depending on the probability value associated with that food source. In this way, the employed bees exchange their information with the onlooker bees. If a position cannot be improved further through the predefined number of cycles called $limit$, then this food source will be abandoned. Assume that the abandoned source is X_i. Then the scout bee produces a food source randomly as in the initialization step to replace with X_i.

3. Enhanced Hybridized Artificial Bee Colony Algorithm

In original ABC algorithm, the convergence speed will decrease when the dimension increases. Bees exchange information on one dimension with a random neighbour in each food source searching process. When dimension increases, the information exchange is limited and its effect is weakened [7]. Many researches showed that the original ABC is poor at exploitation because the initialization population and candidate solutions in the onlooker phase are produced randomly without using other information, such as global best solution. Aim to improve the performance of ABC, in this paper we present a new method by employment of opposition-based learning method, improved onlooker bee search equation with the information of global best solution, and mutation operation.

Algorithm 1 Initial Population Using Opposition-based Learning Method

```
Initialize population size SN, dimension D,the maximum number of function evaluations, Max.FE and limit;
for i = 1 to SN do
    for j = 1 to D do
    |   x_{i,j} = x_{min,j} + rand(0,1)(x_{max,j} - x_{min,j})
    end
end
for i = 1 to SN do
    for j = 1 to D do
    |   ox_{i,j} = x_{min,j} + x_{max,j} - x_{i,j}
    end
end
Select SN solutions with better fitness from X(SN) ⋃ OX(SN) as the initial population;
```

3.1. Initial population using opposition-based learning method

In evolutionary algorithm, population initialization is an important part. Initializing population with random method may not go through the whole space in a certain range that it will decrease the fine search ability and cause premature convergence problem. Aiming at the premature convergence problem of ABC, this paper generates the initial population with the opposition-based learning method [8]. Firstly, generate initial population randomly; then generate opposition solutions for every initial population position; Finally, select SN solutions with better fitness from the two initial populations produced above to conduct the EHABC's initial population. Opposition-based learning method is defined as Algorithm 1.

3.2. Improved onlooker bee search equation

Inspired by PSO algorithm, Zhu et al. proposed an improved ABC algorithm called GABC algorithm by making use of the information of global best solution in the solution search equation to improve the exploitation ability of standard ABC using Eq. 3.1 as follows [5]:

$$v_{i,j} = x_{i,j} + \phi_{i,j}(x_{i,j} - x_{k,j}) + \varphi_{i,j}(x_{best,j} - x_{i,j}) \tag{3.1}$$

where $x_{best,j}$ is the jth element of the global best solution, $\varphi_{i,j}$ is a uniform random number in $[1, 1.5]$.

However, Wei-feng Gao et al. pointed out that since the guidance of the last two terms of Eq. 3.1 may be in opposite directions, it might cause an "oscillation" phenomenon, which would cause inefficiency to the search ability of GABC and delay convergence [9]. Hence, we employed the well-designed search equation to avoid this phenomenon, which was beneficial to enhance the performance of ABC, as Eq. 3.2 shows:

$$v_{i,j} = x_{k,j} + rand(0,1)(x_{best,j} - x_{k,j}) \tag{3.2}$$

where k is an integer randomly select from the range $[1, SN]$ and is also different from i, and X_{best} is the best solution with best fitness in the current population. With the guidance of the only one term $(x_{best,j} - x_{k,j})$ and with X_{best}, Eq.3.2 not only can avoid the oscillation phenomenon, but also enhances the search ability of ABC. By the way, since the vector X_k for generating the candidate solution is chosen from the population randomly and consequently, it has no bias to any special search directions, therefore, Eq.3.2 can try to keep the exploration.

Algorithm 2 The main steps of EHABC

```
Initialize the population of employed bees by using Algorithm 1;
while FE < Max.FE do
    for each employed bee do
        Randomly choose a neighbor employed bee;
        Update the position of employed bee by using Eq. 2.2;
        Calculate the fitness value by using Eq. 2.4;
        Apply greedy selection strategy;
        Update trial counter of the bee;
    end
    Calculate the probability of each food source by Eq. 2.3;
    for each onlooker bee do
        Select an employed bee for improvement its solution according to the probability;
        Randomly choose an employed bee as neighbor;
        Generate the candidate solution of the employed bee by using Eq. 3.2 and the neighbor;
        Calculate the fitness value by using Eq. 2.4;
        Apply greedy selection strategy;
        Update trial counter of the bee;
    end
    /* Mutation bee phase */
    for each food source f_i in food source population do
        Randomly choose two parents different to i from the food source population;
        Generate new food source by Eq. 3.3;
        Calculate the fitness value by using Eq. 2.4;
        Apply greedy selection strategy;
        Update trial counter of the bee;
    end
    if there is an employed bee becomes scout then
        replace it with a new random generated source position;
    end
end
```

3.3. Mutation bee phase

Inspired by the mutation operation of DE and the crossover operation of HABC [10], TRAN Dang Cong et al. proposed a new approach to update the position of individual in mutation bee phase using Eq. 3.3, in which the information of global best solution was employed to further improve the performance of ABC [7]. In this paper, Eq. 3.3 is also applied to the solution search equation of EHABC's mutation bee phase. The search equation in mutation bee phase is modelled as Eq. 3.3.

$$v_{i,j} = rand(0,1)(x_{i,j} - x_{k_1,j}) + rand(0,1)(x_{best,j} - x_{k_2,j}) \tag{3.3}$$

where $x_{k_1,j}$ and $x_{k_2,j}$ are two food sources that are randomly chosen from food source population and i, k_1 and k_2 is mutually different, x_{best} is the global best solution. Not only can this mutation operation improve the algorithm's local search and global search abilities, but also it can make the algorithm be capable to avoid being trapped into local optima.

By applying three methods introduced above, the main steps of EHABC proposed are described in Algorithm 2, where the termination condition is met when the number of Function evaluations (FEs) reaches the predetermined Maximum number ($Max.FE$).

4. Results and Analysis

The performance of EHABC is evaluated on 6 well-known benchmark functions with 10 dimensions over 30 runs, and compared to 4 other ABC variants: canonical ABC [3], GABC [5], HABC [10] and EABC [7]. Table 1 shows the test problems, bounds of the search spaces and the global optimum values for the problems. For fair comparison, all ABC variants are tested using the same settings of parameters, that is, the population size $SN = 40$, $limit = 200$. Furthermore, the maximum number of function evaluations is set to be 2,000. The mean value (mean) and standard deviation values (SD) obtained for test problems are presented in Table 2. What's more, Table 3 displays the average execution time of each method over the benchmark functions.

Table 1: Test problem

Name	Function	Interval	Global Optimum
Sphere	$f_1(X) = \sum_{i=1}^{n} x_i^2$	$[-100, 100]$	$F_{min} = 0$, $X = (0, 0, \ldots)$
Rosenbrock	$f_2(X) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	$[-30, 30]$	$F_{min} = 0$, $X = (1, 1, \ldots)$
Rastrigin	$f_3(X) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	$[-5.12, 5.12]$	$F_{min} = 0$, $X = (0, 0, \ldots)$
Griewank	$f_4(X) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	$[-600, 600]$	$F_{min} = 0$, $X = (0, 0, \ldots)$
Ackley	$f_5(X) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	$[-32, 32]$	$F_{min} = 0$, $X = (0, 0, \ldots)$
Schwefel	$f_6(X) = 418.98288727243369 * n - \sum_{i=1}^{n} x_i \sin(\sqrt{\lvert x_i \rvert})$	$[-500, 500]$	$F_{min} = 0$ $X = (420.9687, 420.9687, \ldots)$

Table 2: Performance comparison of five algorithms with D=10

Function		ABC	GABC	HABC	EABC	EHABC
f_1	Mean	8.47663e-17	5.57133e-17	4.19697e-18	5.23848e-17	**3.49592e-18**
	SD	2.34869e-17	1.44997e-17	2.41693e-18	1.8038e-17	**2.22565e-18**
f_2	Mean	0.404502	0.0905165	0.176567	**0.0379949**	0.0691254
	SD	0.678632	0.19784	0.430975	**0.0506429**	0.183442
f_3	Mean	**0**	**0**	**0**	**0**	**0**
	SD	**0**	**0**	**0**	**0**	**0**
f_4	Mean	0.00277328	0.00174731	0.000282161	0.000271158	**7.31267e-15**
	SD	0.00501418	0.00360317	0.00154546	0.00148519	**4.00531e-14**
f_5	Mean	7.87518e-15	6.69094e-15	**2.42769e-15**	5.50671e-15	4.67774e-15
	SD	1.13631e-15	1.7413e-15	1.79059e-15	1.65589e-15	**9.01352e-16**
f_6	Mean	-8.18545e-13	-9.09495e-13	-6.36646e-13	-8.79178e-13	**-5.76013e-13**
	SD	2.77513e-13	**0**	4.23908e-13	1.6605e-13	4.45773e-13

Table 3: The average execution time of algorithms on each benchmark function

Function	ABC	GABC	HABC	EABC	EHABC
f_1	312.854	313.65	464.307	473.832	467.547
f_2	498.434	573.108	853.865	865.05	757.348
f_3	420.938	496.031	743.252	743.601	748.236
f_4	736.992	735.11	1093.85	950.616	765.901
f_5	565.523	573.04	859.544	861.497	668.027
f_6	539.082	535.744	776.936	796.91	696.294

Through the experiments on 6 test functions with 10D, the results displayed in Table 2 show that EHABC has better performance than other four ABC variants in five out of six benchmark functions, except f_2. According to Table 3, it can be observed that the average execution time of EHABC is not much different than other algorithms. The results obtained by EHABC confirm that the proposed approach can be considered as a viable method for optimization problems.

EHABC obtained these results because of three main reasons: 1) More uniformly distributed initial population with opposition-based learning method; 2) In the onlooker bee phase, each candidate solution learns from the global best solution and a randomly selected solution that improves the global search capability; 3) What's more, in the mutation bee phase, each candidate solution learns from itself and global best solution that enhances the local search capability and global search capability of the algorithm, respectively.

5. Conclusion

This paper proposed a new approach EHABC in order to enhance the original ABC algorithm for global optimization problem. ABC, GABC, HABC, EABC and EHABC algorithms were tested on 6 well-known benchmark problems and results obtained were compared. Experiment results showed that the proposed EHABC could get better exploitation and exploration abilities than the other four ABC variants, and improves the performance of original ABC in terms of accuracy.

In the future, the researchers of this paper will extend the research for the aim of applying EHABC to practical applications, such as public opinion trends prediction problem [11].

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