A Novel Artificial Bee Colony Algorithm

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***Abstract*—Artificial bee colony algorithm is a new population-based evolutionary method based on the intelligent behavior of honey bee swarm. It has shown more effective than other biological-inspired algorithms. However, there are still insufficiencies in ABC algorithm, which is good at exploration but poor at exploitation and its convergence speed is also an issue in some cases. For these insufficiencies, we propose a novel artificial bee colony algorithm (NABC) for numerical optimization problems in this paper to improve the exploitation capability by incorporating the current best solution into the search procedure. Experiments are conducted on a set of unimodal/multimodal benchmark functions. The experiments results of NABC have been compared with Gbest-guided artificial bee colony algorithm (G-ABC), improved artificial bee colony algorithm (I-ABC), Elitist artificial bee colony algorithm (E-ABC). The results show that NABC is superior to those algorithms in most of the tested functions.**

***Keywords*-swarm intelligence; artificial bee colony algorithm; numerical function optimization**

I. INTRODUCTION

In recent years, swarm intelligence has attracted the attention of researchers in they related fields. Researching on swarm intelligence, many intelligence-based optimization algorithms have been developed for different kinds of optimization problems, such as particle swarm optimization inspired by the social behavior of bird flocking or fish schooling [1] and ant colony optimization (ACO) inspired by the foraging behavior of ant colonies [2]. Inspired by the intelligent foraging behavior of honey bees, Yang proposed a virtual bee algorithm (VBA) to solve the numerical optimization problems [3] and Karaboga [4] proposed the artificial bee colony (ABC) algorithm. Comparing with GA [5], ACO, PSO, Differential Evolution [6] and other evolutionary algorithms [7; 8], ABC is competitive due to its simplicity, robustness, ease of implementation, good convergence properties and more effective. It has gained a lot of interest since its invention in 2005, and ABC algorithm has adopted by researchers in various research fields [9-15].

ABC algorithm has been shown to be a promising, well-performed optimization algorithm. However, it still has some limitations. For example, the process of generate new candidate solutions in ABC algorithm is grounded on the information of previous solutions, and its convergence speed is also an issue in some cases. The reason for these insufficiencies is that ABC is good at exploration but poor at exploitation [16].

Therefore, in order to achieve good performances of ABC, a number of variant ABC algorithms are proposed in recent years to achieve these goals, such as Banharsakun et al. proposed a best-so-far ABC by modified the solution search equation [13]; Zhu and Kwong proposed the Gbest-guided ABC (GABC) by employing the global best solution to modified the search process [12]; Gao and Liu proposed IABC [15] by using a modified solution search equation together with a novel chaotic initialization. Comparing with the classical ABC algorithm these modified or improved artificial bee colony algorithms have shown a better performance. However, these modified ABC algorithms also have some shortages. For example, the Chaotic bee colony algorithm can brings in more extra function evaluations in chaotic search and the others have an issue on the convergence precision together with convergence speed on some of the tested functions.

In this paper, we propose a novel artificial bee colony algorithm (NABC) for numerical optimization to improve the exploitation capability by incorporating best solution into the search process. The proposed NABC can achieve high-quality solutions for most of the tested functions with fast convergence speed.

II. ANALYSIS OF THE ARTIFICIAL BEE COLONY ALGORITHM

In the ABC algorithm, the position of a food source represents a possible solution of the optimization problem and the profitability of a food source corresponds to the quality (fitness) of the associated solution. At the first step, randomly distributed SN food source positions are generated. SN denotes the size of population and it is equal to the number of employed bees. In the basic ABC, the fitness function in minimization problems is defined as

$$fit_i = \begin{cases} \frac{1}{1+f_i}, & f_i \geq 0 \\ 1+|f_i|, & f_i < 0 \end{cases} \quad (1)$$

where f_i denotes the objective function value of solution i,

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while fit_i is the relevant fitness value of solution i.

An onlooker bee chooses a food source according to the roulette wheel selection. The probability value P_i, associated with food source, is given by

$$P_i = \frac{fit_i}{\sum\limits_{j=1}^{SN} fit_j} \tag{2}$$

To produce a candidate food position from the old one in memory, the classical ABC uses Eq.(3),

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

The scout discovers a new food source randomly according to:

$$x_{i,j} = x_{min,j} + rand(0,1)(x_{max,j} - x_{min,j}) \tag{4}$$

where $j \in \{1, 2, \ldots, D\}$

III. The Novel Artificial Bee Colony Algorithm

A. Modified Search Strategy

Both exploitation and exploration are very important for the population-based optimization algorithms. In these optimization algorithms, the ability of the exploitation is to find the global best value while the ability of exploration is to look for better solutions in numerous unknown sector of the solution space. However the exploration and exploitation contradicts to each other in practice. In order to achieve good optimization performance, the two abilities should be well balanced. According to the search equation of ABC algorithm which is described by Eq. (3), the new candidate solution is generated by moving the old solution towards another solution selected randomly from the population. But, as the probability that generate a good solution is similar to generate a bad solution, so the new candidate solution is not definitely better than the previous one. What is more, the ability of exploration in Eq. (3) is random enough. All in all, the search equation of ABC is good at exploration but poor at exploitation.

Inspired by DE, in order to overcome the limitation, we modify the solution search equation by incorporating best solution into the search process. The operation process as follows

$$v_{ij} = x_{ij} + (1 - \varphi)(x_{kj} - x_{ij}) + \varphi(Gbest_j - x_{ij}) \tag{5}$$

where $\varphi \in (0, 1)$ and $Gbest_j$ is the best solution in the current population, the best solution in the current population can lead the new candidate solution to the best, namely, improve the exploitation performance of ABC algorithm.

In this paper, we modify ABC algorithm by using Eq. (5) replaced Eq. (3). We refer to this modified ABC algorithm as NABC. Although, the search equation of NABC algorithm described by Eq. (5) is similar to the equation of DE [6], while the characteristic of ABC algorithm in NABC distinguish it from DE. The whole of NABC algorithm consists of three different phases, employed bee phase, onlooker phase and scout bee phase. Comparing with the DE, there has much in common in the employed bee phase, except NABC does not include the crossover stage. Furthermore, the onlooker phase and scout bee phase are much different from the DE. In the two phases the NABC algorithm has the ability of update the selected solution and generates a new solution to replace the abandon one.

IV. Experiments

In order to test the performance of NABC algorithm on numerical function optimization, ten numerical benchmark functions are used here, as shown in Table 1. The experiment results are compared with other evolutionary algorithms and recent state-of-the-art modified ABC algorithms. Those evolutionary algorithms included standard PS-EA, standard GA and standard ABC, while those improved ABC algorithms used to compare are EABC, GABC and IABC. Additionally, we follow the parameter settings in the original paper of EABC [16], GABC [12], IABC [15]. Each of the experiments is repeated 30 times independently. The best results are marked in bold.

TABLE I BENCHMARK FUNCTION USED IN EXPERIMENTS

Function Number	Function Name	lb	ub	Best Value
F1	Schaffer	-100	100	0
F2	Rosenbrock	-50	50	0
F3	Griewank	-600	600	0
F4	Sphere	-100	100	0
F5	Ackley	-32.768	32.768	0
F6	Rastrigin	-5.12	5.12	0
F7	Schwefel	-500	500	0
F8	Schwefel1.2	-100	100	0
F9	Schwefel2.21	-100	100	0
F10	Noncontinuous Rastrigin	-5.12	5.12	0

A. Compare NABC with classical ABC, PS-EA, GA

In this section, we compared NABC with classical ABC and other evolutionary algorithms such as PS-EA and GA. The benchmark functions and the maximum numbers of cycles proposed in [14] were used in this part. As is shown in Table II, the NABC algorithm offers the best performance on most of the test functions. In particular, it offers the highest accuracy on F3 and F6 compared with other algorithms. In addition, as the Figures 1 and 2 shows, the exploitation process in NABC is efficient than the compared algorithms in this part.

B. Compare NABC with IABC, EABC and GABC

In this part, we compared with recent state-of-the-art modified ABC algorithms. Firstly, compared with IABC, as the results of other functions are not obvious, we select 7 benchmark function with the same number of 5.0104 function evaluations (FEs) for each test function [15]. Then, NABC is further compared with (GABC) in [12] and EABC in [17]. NABC and EABC follow the parameter settings in the original paper of GABC [12]. Each algorithm is repeated 30 runs independently.

As is shown in Table III, the NABC offers the best performance on most benchmark function. In particular, comparing with IABC, it offers the high accuracy on F8 and F9. The NABC algorithm can also find the optimal solutions on the complex multimodal functions, such as, F3, F6 and F10. Although the performance of NABC on F4 is not better than IABC, but the results are much closer to the optimal solution. In addition, NABC shows faster convergence speed on F6, F8, F9 and F10. Therefore, it can be concluded that NABC is more efficient compared with IABC.

In Table IV, NABC can obtain much better solutions those functions, i.e., F1, F2, F3, F5 and F6. However, EABC is better than NABC on F4 on the dimension of 30 and on the test function they four algorithm are equal when the dimension equals 2. Although NABC could not find better solutions than EABC in F4, the NABC could have a more efficiency and better search ability than EABC and GABC on most functions. In a word, the superiority of EABC to NABC is not very obvious.

From Tables II-IV, it is clear that NABC works better in most cases and achieves better performance than those mentioned algorithms.

V. CONCLUSIONS

In this paper, we propose a modified ABC algorithm called NABC by referring to existing superb solutions to optimize the search process. Compared with different types of modified ABC algorithms, the results show that NABC doesn't lose to those mentioned algorithms on most functions. As future expected, NABC will be applied in more complex optimization problems like data mining, flow shop scheduling problem, vehicle routing problem, and so on.

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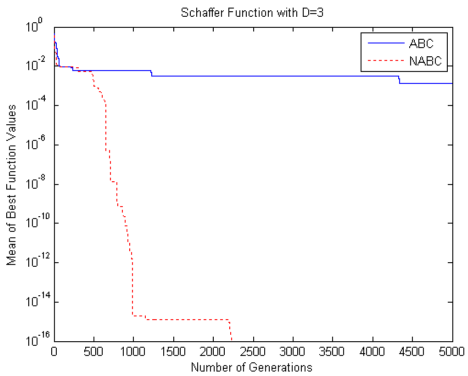

Figure. 1: Convergence curves of ABC and NABC algorithms for F1

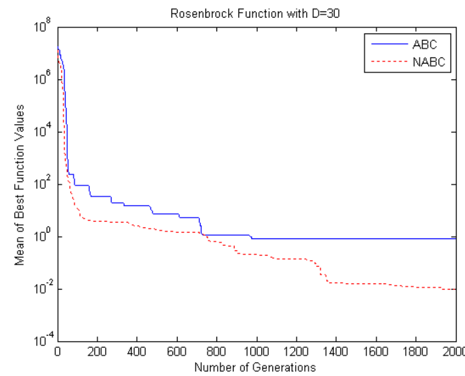

Figure. 2: Convergence curves of ABC and NABC algorithms for F2

TABLE II. RESULTS OBTAINED BY GA, PS-EA, ABC AND NABC ALGORITHMS

Function	Alg	GA		PS-EA		ABC		NABC	
	Dim	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
F2	10	46.3184	33.8217	25.303	29.7964	0.034072	0.045553	**0.0040**	0.0043
	20	103.93	29.505	72.452	27.3441	0.13614	0.132013	**0.0030**	0.0039
	30	166.283	59.5102	98.407	35.5791	0.219626	0.152742	**0.0014**	0.0024
F3	10	0.050228	0.029523	0.222366	0.0781	0.00087	0.002535	**0**	0
	20	1.0139	0.026966.	0.59036	0.2030	2.01e-08	6.76e-08	**0**	0
	30	1.2342	0.11045	0.8211	0.1394	2.87e-09	8.45e-10	**0**	0
F5	10	0.59267	0.22482	0.19209	0.1951	7.8e-11	1.16e-09	**5.2e-015**	1.7e-015
	20	0.92413	0.22599	0.32321	0.097353	1.6e-11	1.9e-11	**2.0e-013**	2.4e-014
	30	1.0989	0.24956	0.3771	0.098762	**3e-12**	5e-12	1.9e-011	7.6e-012
F6	10	1.3928	0.76319	0.43404	0.2551	0	0	**0**	0
	20	6.0309	1.4537	1.8135	0.2551	1.45e-08	5.06e-08	**0**	0
	30	10.4388	2.6386	3.0527	0.9985	0.033874	0.181557	**0**	0
F7	10	1.9519	1.3044	0.32037	1.6185	1.27e-09	4e-12	**1.27e-004**	2.9e-020
	20	7.285	2.9971	1.4984	0.84612	19.83971	45.12342	**2.55e-004**	6.3e-010
	30	13.5346	4.9534	3.272	1.6185	146.8568	82.3144	**3.82e-004**	2.7e-007

TABLE III. PERFORMANCE COMPARISONS OF NABC AND IABC

Function	Alg	Global Min		IABC	NABC
F2	100	0	Mean	2.83e+02	**63.8363**
			S.D.	8.94e+01	39.0168
F3	30	0	Mean	0	**0**
			S.D.	0	0
F4	30	0	Mean	**0**	5.3357e-016
			S.D.	0	1.1279e-016
F6	30	0	Mean	0	**0**
			S.D.	0	0
F8	30	0	Mean	6.47e-03	**2.4736e-007**
F6			S.D.	9.25e-03	3.5209e-007
F9	30	0	Mean	6.63e-03	**1.6846e-016**
			S.D.	1.92e-02	2.6417e-016
F10	30	0	Mean	4.50e-15	**0**
			S.D.	5.79e-15	0

TABLE IV. PERFORMANCE COMPARISONS OF NABC, GABC AND IABC

Function	Alg	G-ABC		EABC		NABC	
	Dim	Mean	S.D	Mean	S.D.	Mean	S.D.
F1	2	0	0	0	0	**0**	0
	3	1.850371e-18	1.013e-17	2.79e-07	2.24e-07	**0**	0
F2	2	1.684969e-04	1.454e-04	4.63e-04	4.57e-04	**6.9487e-005**	7.5883e-005
	3	2.659139e-03	2.220e-03	1.20e-02	7.06e-03	**0.0020**	0.0017
F3	30	2.960594e-17	4.993e-17	4.90e-14	7.31e-03	**0**	0
	60	7.549516e-16	4.127e-16	4.19e-14	9.05e-03	**0**	0
F4	30	4.176106e-16	7.365e-17	**1.67e-16**	2.70e-16	4.1413e-016	8.7636e-017
	60	1.433867e-15	1.375e-16	1.41e-15	1.82e-15	**1.2635e-015**	1.0787e-016
F5	30	3.215205e-14	3.252e-15	1.22e-10	4.86e-11	**2.6468e-014**	3.3704e-015
	60	1.000088e-13	6.089e-15	1.55e-07	2.84e-08	**7.1942e-014**	4.8104e-015
F6	30	1.326346e-14	2.445e-14	9.97e-15	3.87e-15	**0**	0
	60	3.524291e-13	1.243e-13	7.51e-13	6.15e-13	**0**	0