

Adaptive Population Artificial Bee Colony for Numerical Optimization

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Abstract—In this paper, an adaptive population artificial bee colony (APABC) is proposed. In APABC, the population size of proposed ABC variant is not a fix but variable. The population size of APABC will be dynamically increased or decreased by population manager according to current solution searching status. It can enhance bees' searching ability and increase population utilization. Thus, In order to test the efficiency of proposed method, fifteen test functions of CEC 2005, which include uni-modal and multi-modal functions, are adopted to test proposed method and compare it with original ABC. From the results, it can be observed that the APABC performs better on most test functions with 50 dimensions.

Keywords- adaptive population; artificial bee colony; cross-over; numerical optimization; population manager

I. INTRODUCTION

In last four decades, there are many classic optimizers were proposed for deal with real-world optimization problems. Such as, genetic algorithm (GA) [1], ant colony optimization (ACO) [2], particle swarm optimization (PSO) [3] and differential evolution (DE) [4] etc.

In 2005, the artificial bee colony (ABC) algorithm was first proposed by Karaboga [5]-[6]. It involves bees' foraging model and simulated bees' forage behavior. The ABC algorithm is consisted of three basic elements, employed bees, onlooker bees and scouts bees. The employed bee and onlooker bee will try to find food (better solution). If employed and onlooker bees cannot find any food, then, the scout bee will start over for following food searching process and for finding new food source.

In recent years, more and more researchers are studying on ABC algorithms either enhancement or applications. In 2012, El-Abd proposed an interesting ABC variant named GOABC [7]. They introduced an opposition-based learning and involved generalized concept into ABC for enhancing optimizer's performance. The GOABC exhibits good results on solving both uni-modal and multi-modal test functions.

In the same year, Yu Liu *et al.* proposed an improved ABC algorithm with mutual learning (mutual learning ABC) [8] whose mutual learning factor will select two bees and to adjust the produced candidate food source with the higher fitness.

Besides, Yan *et al.* proposed hybrid artificial bee colony (HABC) algorithm [9], which involved GA's crossover operator to improve bees' information exchange.

In order to improve ABC's convergence performance, recently, Xiang and An proposed efficient and robust artificial bee colony (ERABC) [10]. In ERABC, a combinatorial solution search is proposed to enhance bees' search ability. Also, the chaotic search technique is adopted for scout bee to keep the population diversity and avoid bees being trapped in local optimum. Both strategies can speed up solution searching process.

Although, there are so many ABC variants were proposed. In fact, there is no way to know what suitable population size is for solving current problem until now. In order to solve this problem, in this paper, the population manager is involved to artificial bee colony (ABC) algorithm to increase or decrease population size according current solution searching status.

This paper is consisted of five parts. The basic concept of ABC algorithm is introduced in section II. The detail of proposed method is presented in section III. The experiments results are presented in section IV. Finally, the conclusions are described in section V.

II. ARTIFICIAL BEE COLONY SELECTING

Artificial bee colony (ABC) algorithm is a novel numerical optimizer which is to simulate bees' foraging behavior in solution space for finding global optimal solution in reasonable criteria. In ABC, there are two different kinds of bees, which are employed and onlooker bees, will try to find new food source (also named solutions). The food searching process will be performed by following equation.

$$v_{i,j} = x_{i,j} + \phi_{i,j} \times (x_{i,j} - x_{k,j}) \quad (1)$$

where i and k is a random integer between $[1, ps]$, i and k are two random selected bees and i is not equal to k . The ps represents population size. The j is also a random integer between $[1, D]$, the D denotes dimension of problems. The $\phi_{i,j}$ is a normal distribution number between $[-1, 1]$, x and v are current food source and new food source, respectively.

For onlooker bees, food source selection is according to probability which is obtained by equation (2). Similar to employed bees, onlooker bees performs food searching process also use equation (1).

$$p_i = \frac{fit_i}{\sum_{n=1}^{PS} fit_n} \quad (2)$$

where fit_i is fitness value and i denotes the i_{th} bee. The fitness value will be updated by following equation.

$$fit_i = \begin{cases} \frac{1}{(1+fit_i)}, & \text{if } fit_i \geq 0 \\ 1 + \text{abs}(fit_i), & \text{if } fit_i < 0 \end{cases} \quad (3)$$

where f_i represents objective value of i_{th} bee. If there is no better food source can be found within g generations, the scout bees will then handle the food search process and new food source will be random produced by following equation.

$$x_i^{rand} = lb + \text{rand}(0,1)(ub - lb) \quad (4)$$

where x_i^{rand} denotes a new random produced bee, and lb and ub are the lower and upper boundary of search range respectively.

The procedure of ABC algorithm is listed as follows.

- Step 1: Initialization for generated food source randomly.
- Step 2: Fitness Evaluations.
- Step 3: Employed bees looking for new food source by (1) and evaluate x_i and v for select better food source.
- Step 4: Calculate probability of fitness value by (2).
- Step 5: Onlooker bees will select food source by roulette wheel and keep looking for better food by (1).
- Step 6: Fitness Evaluations.
- Step 7: Record the global best food source (G_{best}).
- Step 8: If there is no better can be found within limited generations, scout bee will then be activated and try to search new food source.
- Step 9: Repeat step 3 to 8, until terminal condition is reached.

III. PROPOSED METHOD

There are several parameters need to be setup before apply the ABC to solve optimization problems, such as reasonable population size. A population contains more bees can extend searching area and increase probability for finding the global optimal solution in solution space, but it will spend more time in iteration and vice versa. Unfortunately, there is no way to know how many bees in the population are suitable for solving current problem until now. It usually depended on users' experience or complexity of the problem.

According to our previous works [11]-[12], the population manager can efficiently improve population utilization for GA and PSO. In this paper, the population manager is involved to ABC, which will increase or decrease bees according to the

solution searching status, to enhance ABC's searching ability. Thus, the population size in the proposed method is variable.

Besides, after numerous generations, most bees may be trapped into the local minimum during the searching process, or need a competent guide to lead them toward the potential area. Thus, the information (experience) of existing bees may be too less to handle the current solution searching procedures. Thus, new bees should be joined into the population to speed up the solution searching progress. In order to avoid unlimited increase or decrease in bees, the upper and lower boundary for population size should be predefined.

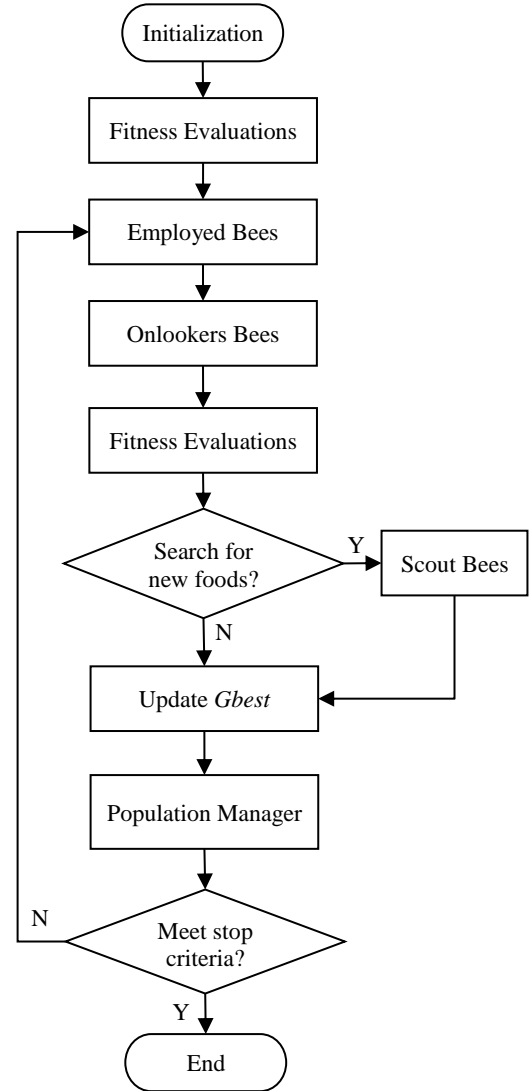


Fig. 1. Flowchart of the proposed method

The population manager will adjust population size in following three conditions:

- 1) If the bees cannot find any better solution in current generation, and the current population size doesn't equal or exceed the upper boundary. A pair of new bee will be added

into the population. The new bees will be created from combining the information of two randomly selected bees, through a crossover-like information combination strategy to provide useful information for these bees. That is, the two bees will be placed at a beneficial position to the population and involved in the solution searching process in the following generation.

2) If the bees can find one or more better solutions in current generation, and the current population size doesn't equal or less than the lower boundary. The existing bees may with ability to handle the current solution searching procedures. The redundant bees should be expelled from the population to conserve their evolution time for speeding up the solution searching progress. Thus, a pair articles with poor performance in the current iteration will be removed from the population. In the following iteration, the bee number will be two less previous iteration.

3) If the bees cannot find any better solution in current generation, but current population size reaches the upper or lower boundary. The population size will not be change.

The complete flowchart of the proposed method is shown in Fig. 1. After all bees in the population have moved, the population manager will determine the elimination of a redundant bees with poor performance, generate a pair of bees, or the maintenance of the current population size according to the solution-searching status. All bees in the population will perform the next generation after the population manager.

IV. EXPERIMENTS

A. Test Functions

In order to test the performance of proposed method and compare it with original ABC, fifteen test function of CEC 2005 [13], which include uni-modal functions ($F_1 \sim F_5$) and multi-modal functions ($F_6 \sim F_{15}$), are selected for experiments. All the test functions are set as 50 dimensions. The names and types of the selected test function are listed in Table I.

TABLE I. FIFTEEN SELECTED TEST FUNCTIONS OF CEC 2005

f	Test Functions
f_1	Shifted Sphere Function
f_2	Shifted Schwefel's Problem 1.2
f_3	Shifted Rotated High Conditioned Elliptic Function
f_4	Shifted Schwefel's Problem 1.2 with Noise in Fitness
f_5	Schwefel's Problem 2.6 with Global Optimum on Bounds
f_6	Shifted Rosenbrock's Function
f_7	Shifted Rotated Griewank's Function without Bounds
f_8	Shifted Rotated Ackley's Function with Global Optimum on Bounds
f_9	Shifted Rastrigin's Function
f_{10}	Shifted Rotated Rastrigin's Function
f_{11}	Shifted Rotated Weierstrass Function

f_{12}	Schwefel's Problem 2.13
f_{13}	Expanded Extended Griewank's plus Rosenbrock's Function (F8F2)
f_{14}	Shifted Rotated Expanded Scaffer's F6
f_{15}	Hybrid Composition Function

The search range and global optimum of all test functions are listed in Table II.

TABLE II. GLOBAL OPTIMUM AND SEARCH RANGE OF FIFTEEN TEST FUNCTIONS

f	Global Optimum	Search range
f_1	-450	$[-100, 100]^D$
f_2	-450	$[-100, 100]^D$
f_3	-450	$[-100, 100]^D$
f_4	-450	$[-100, 100]^D$
f_5	-310	$[-100, 100]^D$
f_6	-390	$[-100, 100]^D$
f_7	-180	$[0, 600]^D$
f_8	-140	$[-32, 32]^D$
f_9	-330	$[-5, 5]^D$
f_{10}	-330	$[-5, 5]^D$
f_{11}	90	$[-0.5, 0.5]^D$
f_{12}	-460	$[-\pi, \pi]^D$
f_{13}	-130	$[-3, 1]^D$
f_{14}	-300	$[-100, 100]^D$
f_{15}	120	$[-5, 5]^D$

In order to easier compare the performance between both ABCs, the error value e between the real global optimum f^* and function value f found by optimizer will be presented. The error value can be calculated as follows.

$$e = f - f^* \quad (5)$$

B. Parameters Setting

In the experiments, the original ABC is conducted to compare with the proposed method. In order to fair comparison, all the parameters are according to their original settings. The initial population size of both proposed method and original ABC is set as 250. The initial population is set as 250. The upper and lower boundary of population size of population manager is set as 400 and 100 respectively. The maximum Fitness Evaluations (FEs) are set as 500,000.

C. Experiment Results

In experiments, both APABC and original ABC are executed for 25 independent runs. The experiment results are listed in Table III which presents the mean and standard deviation of error value e . The best results among the two ABC variants are shown in bold.

TABLE III. EXPERIMENT RESULTS FOR 50D TEST FUNCTIONS

Algorithms Results	f_1	f_2	f_3	f_4	f_5	
ABC	Mean	9.4884E+02	4.7303E+04	7.6691E+07	4.9125E+08	3.1264E+04
	Std.	3.5065E+02	4.5119E+03	1.0942E+07	9.5546E+06	2.7450E+03
Proposed Method	Mean	1.0429E-09	4.5815E+04	6.1768E+07	8.5348E+07	1.6552E+04
	Std.	2.3769E-09	6.4391E+03	1.0032E+07	1.1180E+08	1.2760E+03
Algorithms Results	f_6	f_7	f_8	f_9	f_{10}	
ABC	Mean	3.3300E+04	6.1954E+03	2.1275E+01	2.2478E+01	1.2257E+03
	Std.	3.0981E+04	2.1196E-02	4.6243E-02	2.2991E+00	1.2127E+02
Proposed Method	Mean	1.1632E+03	6.1953E+03	2.1272E+01	1.2801E+01	4.4782E+02
	Std.	3.5480E+03	3.4225E-03	3.1579E-02	2.6700E+00	4.9565E+01
Algorithms Results	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	
ABC	Mean	6.4449E+01	2.9914E+05	1.0990E+04	2.3828E+01	9.7577E+01
	Std.	3.5780E+00	5.0391E+04	6.7594E+03	1.4140E-01	1.4014E+01
Proposed Method	Mean	6.2929E+01	3.0797E+05	6.4127E+00	2.3901E+01	9.5550E+01
	Std.	2.4482E+00	7.9149E+04	7.8791E-01	1.9907E-01	2.8501E+01

From the results, it can be observed that the proposed method performed better on all the uni-modal functions, and on most test multi-modal functions. Except the functions 12 and 14, the proposed method performed similar results as original ABC.

V. CONCLUSIONS

In this paper, the population manager is involved to enhance efficiency of population member's utilization. It can make bees easier to find the better solutions.

Fifteen test functions of CEC 2005, which includes uni-modal and multi-modal functions, were adopted for experiments through a reasonable average and fitness evaluations. From the results, it can be observed that the proposed APABC can find better solutions than original ABC for solving most test functions.

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