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Artificial Bee Colony Algorithm Based on Von Neumann Topology Structure

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Abstract—Article Bee Colony (ABC) is one of the most recently introduced algorithms based on the intelligent foraging behavior of a honey bee swarm. This paper proposes a new variant of the ABC algorithm based on Von Neumann topology structure for solving global optimization problems, namely Von Neumann Neighborhood Article Bee Colony (VABC). VABC significantly improves the original ABC in solving complex optimization problems. In this work, VABC algorithm is used for optimizing a set of widely-used benchmark functions and the comparative results produced by ABC. The simulation results showe that the proposed VABC outperforms the original ABC algorithms in terms of accuracy, robustness and convergence speed.

Keywords-component; Article Bee Colony; Von Neumann topology; Swarm Intelligence;

1. Introduction

Swarm Intelligence (SI) is an innovative artificial intelligence technique for solving complex optimization problems. In recently years, many SI algorithms have been proposed, such as Ant Colony Optimization (ACO) [1], Particle Swarm Algorithm (PSO) [2], and Bacterial Foraging Optimization (BFO) [3]. Artificial Bee Colony (ABC) algorithm is a new swarm intelligent algorithm, which was first introduced by Karaboga in Erciyes University of Turkey in 2005 [4], and the performance of ABC is analyzed in 2007 [5]. The ABC algorithm imitates the behaviors of the real bees on searching food source and sharing the information of food sources to the other bees. Since the ABC algorithm is simple in concept, easy to implement, and has fewer control parameters, it has been widely used in many fields, such as constrained optimization problems [6], neural networks [7] and clustering [8].

In [9][10], James Kennedy et al. had introduced the effects of various population topologies on the PSO algorithm in detail and they considered that the PSO with Von Neumann configuration performed more better than the other topologies structure. Hence, this paper applies Von Neumann topology structure to the ABC. In order to evaluate the performance of the VABC, we compared the performance of the VABC algorithm with that of ABC on a set of well-known benchmark functions. From the simulation results, the VABC algorithm shows remarked performance improvement over the ABC algorithm in all benchmark functions.

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The rest of the paper is organized as follows. In Section Ⅱ， we will introduce the original ABC algorithm. Section Ⅲ will discuss the Von Neumann topology structure, and our Von Neumann topology implementations of the ABC algorithm will be presented. Section Ⅳ tests the algorithms on the benchmarks, and the results obtained are presented and discussed. Finally, conclusions are given in Section Ⅴ.

2. The Original Article Bee Colony Algorithm

The artificial bee colony algorithm is a new population-based metaheuristic approach, initially proposed by Karaboga [4][5] and further developed by Karaboga and Basturk [6][7]. It has been used in various complex problems. The algorithm simulates the intelligent foraging behavior of honey bee swarms. It is a very simple and robust optimization algorithm. In the ABC algorithm, the colony of artificial bees is classified into three categories: employed bees, onlookers and scouts. Employed bees are associated with a particular food source which they are currently exploiting or are "employed" at. They carry with them information about this particular source and share the information to onlookers. Onlooker bees are those bees that are waiting on the dance area in the hive for the information to be shared by the employed bees about their food sources, and then make decision to choose a food source. A bee carrying out random search is called a scout. In the ABC algorithm, first half of the colony consists of the employed artificial bees and the second half includes the onlookers. For every food source, there is only one employed bee. In other words, the number of employed bees is equal to the number of food sources around the hive. The employed bee whose food source has been exhausted by the bees becomes a scout. The position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution represented by that food source. Onlookers are placed on the food sources by using a probability based selection process. As the nectar amount of a food source increases, the probability value with which the food source is preferred by onlookers increases, too [4][5]. The main steps of the algorithm are given in Table 1:

In the initialization phase, the ABC algorithm generates a randomly distributed initial food source positions of *SN* solutions, where *SN* denotes the size of employed bees or onlooker bees. Each solution x_i (i =1, 2,..., *SN*) is a *D*-dimensional vector.

TABLE I. MAIN STEPS OF THE ABC ALGORITHM

1:cycle=1
2:Initialize the food source positions x_i , i =1 ...*SN*
3:Evaluate the nectar amount (fitness fit_i) of food sources
4:**repeat**
5: Employed Bees' Phase
For each employed bee
Produce new food source positions v_i
Calculate the value fit_i
Apply greedy selection mechanism
EndFor.
6: Calulate the probability values p_i for the solution.
7: Onlooker Bees' Phase
For each onlooker bee
Chooses a food source depending on p_i
Produce new food source positions v_i
Calculate the value fit_i
Apply greedy selection mechanism
EndFor
8: Scout Bee Phase
If there is an employed bee becomes scout
Then replace it with a new random source positions
9: Memorize the best solution achieved so far
10 cycle=cycle+1.
11:**until** cycle=Maximum Cycle Number

Here, D is the number of optimization parameters. And then evaluate each nectar amount fit_i . In the ABC algorithm, nectar amount is the value of benchmark function.

In the employed bees' phase, each employed bee finds a new food source v_i in the neighbourhood of its current source x_i . The new food source is calculated using the following equation (1):

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

where $k \in (1, 2, ..., SN)$ and $j \in (1, 2, ..., D)$ are randomly chosen indexes, and k has to be different from i. ϕ_{ij} is a random number between [-1,1]. And then employed bee compares the new one against the current solution and memorizes the better one by means of a greedy selection mechanism.

In the onlooker bees' phase, each onlooker chooses a food source with a probability which related to the nectar amount (fitness) of a food source shared by employed bees. The probability is calculated using the following equation (2):

$$p_i = fit_i / \sum_{n=1}^{SN} fit_i \tag{2}$$

In the scout bee phase, if a food source can not be improved through a predetermined cycles, called "limit", it is removed from the population and the employed bee of that food source becomes scout. The scout bee finds a new random food source position using the equation (3) below:

$$x_i^j = x_{\min}^j + rand[0,1](x_{\max}^j - x_{\min}^j) \tag{3}$$

where $x_{\min}^j$ and $x_{\max}^j$ are lower and upper bounds of parameter j , respectively.

These steps are repeated through a predetermined number of cycles, called Maximum Cycle Number (MCN), or until a termination criterion is satisfied [4][5][11].

3. Article Bee Colony Algorithm based on von neumann topology structure

The essence of driving swarm algorithm activity is social communication. The individual of the swarm will communicate their knowledge with their neighborhoods. Hence, the different concepts for neighborhood lead to different neighborhood topologies. Different neighborhood topologies primarily affect the communication abilities. Some kinds of population structures work well on some functions, while other kinds work well better on other functions. In [10], Kennedy theorized that populations with fewer connections might perform better on highly multimodal problems, while highly interconnected populations would be better for unimodal problems. After studying the various population topologies on the PSO performance, Kennedy considered that Von Neumann topology structure worked well on a wide range of problems [10]. Actually, the original ABC algorithm is a star topolgy structure, which is a fully connected neighhor relation. From equation (1), we noticed that k could be every particle except i. That means every particle is neighbor of *ith* particle. Because of Kennedy's studying, in this paper, we will we apply Von Neumann topology structure to the ABC, namely VABC.

Von Neumann topology was proposed by Kennedy and Mendes [10]. In the Von Neumann topolgy structure, an individual can communicate with four of its neighbors using a rectangular lattice topology. A graphical representation of the Von Neumann model and the star model is shown in Figure 1.

In order to form the Von Neumann topology structure for M particles, we adopt below approch:

(A) Arrange the *M* particles in *rows* rows and *cols* columns, that is *M=rows*cols*

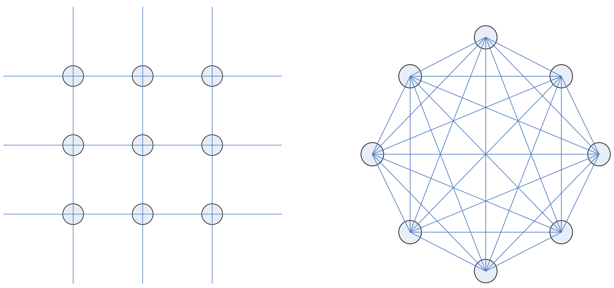

Fig.1. The Von Neumann neighborhood structure is shown on the left and the star neighborhood structure is shown on the right.

(B) For the ith particle, $i \in \{1, 2, \ldots, M\}$:

a) Above neighbor: $N_i(1)$ = (i-$cols$) mod M, if $N_i(1)$ = = 0, $N_i(1)=M$

b) Left neighbor: $N_i(2)$ = i-1, if (i-1) mod $cols$ = = 0, $N_i(2)$ = i–1+$cols$.

c) Right neighbor: $N_i(3)$ = i+1, if i mod $cols$ = = 0, $N_i(3)$ = i+1-$cols$.

d) Below neighbor: $N_i(4)$ = (i+$cols$) mod M, if $N_i(4)$ = = 0, $N_i(4)=M$

Notice the negative number in mod calculation: (-5) mod 20 = 15 [12]

In the VABC algorithm, in the employed bees' phase, we use Von Neumann topology. In the equation (1), k could only be the above, left, below right neighbor of particle i. However, in the onlooker bees' phase, we don't change the original ABC algorithm. This will improve convergence speed.

4. Experiments

4.1. Benchmark functions

In order to compare the performance of the proposed VABC algorithm with ABC, we used a set of well-known benchmark functions. The formulas and the properties of these functions are listed as follows

Sphere function:

$$f_1(x) = \sum_{i=1}^{D} x_i^2$$

$$x \in [-5.12, 5.12]$$

Rosenbrock function:

$$f_2(x) = \sum_{i=1}^{D} 100(x_i^2 - x_{i+1})^2 + (1 - x_i)^2$$

$$x \in [-15, 15]$$

Griewank function:

$$f_3(x) = \frac{1}{4000}\left(\sum_{i=1}^{D} x_i^2\right) - \left(\prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right)\right) + 1$$

$$x \in [-600, 600]$$

Rastrigin function:

$$f_4(x) = \sum_{i=1}^{D} (x_i^2 - 10\cos(2\pi x_i) + 10)$$

$$x \in [-15, 15]$$

Ackley function:

$$f_5(x) = 20 + e - 20\exp(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}) - \exp(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i))$$

$$x \in [-32.768, 32.768]$$

Schwefel function:

$$f_6(x) = D * 418.9829 + \sum_{i=1}^{D} -x_i \sin(\sqrt{|x_i|})$$

$$x \in [-500, 500]$$

Weierstrass function:

$$f_7(x) = \sum_{i=1}^{D}\left(\sum_{k=0}^{k\max}\left[a^k \cos(2\pi b^k (x_i + 0.5))\right]\right) - D\sum_{k=0}^{k\max}\left[a^k \cos(2\pi b^b \cdot 0.5)\right]$$

$$x \in [-0.5, 0.5], a = 0.5, b = 3, k\max = 20$$

Noncountinuous Rastrigrin function:

$$f_8 = \sum_{i=1}^{D}\left(y_i^2 - 10\cos(2\pi y_i) + 10\right)$$

$$y_i = \begin{cases} x_i & |x_i| < \frac{1}{2} \\ \frac{round(2x_i)}{2} & |x_i| >= \frac{1}{2} \end{cases} \quad for\ i = 1, 2, \ldots, D; \quad x \in [-5.12, 5.12]$$

SumSquares function:

$$f_9(x) = \sum_{i=1}^{D} i \cdot x_i^2$$

$$x \in [-10, 10]$$

Schewfel2.22 function:

$$f_{10}(x) = \sum_{i-1}^{D} |x_i| + \prod_{i=1}^{D} |x_i|$$

$$x \in [-10, 10]$$

Dixon-Price function:

$$f_{11}(x) = (x_1 - 1)^2 + \sum_{i=2}^{D} i \cdot (2x_i^2 - x_{i-1})^2$$

$$x \in [-10, 10]$$

4.2. Simulation Results for Benchmark Functions

In the experiment, all functions are tested on 30 dimensions; and the population size of VABC algorithm and ABC algorithm was 100. The experimental results, including the mean and standard deviation of the function values found in 30 runs are proposed in Table 2 and the two algorithms were terminated after 1,000 generation.

From Table 2, the VABC algorithm is better than the ABC algorithms on all functions. On f_2, f_6, f_7 and f_{11} functions, both ABC and VABC algorithms are almost the same. On f_4 and f_8 functions, in the experiment, we found that the best value of the fitness functions for ABC algorithm is as good as VABC algorithm. However, ABC algorithm is easy trapped at loacl optimum, so the average value is worse than VABC. This means that the ability of VABC algorithm getting rid of local minima is very strong. On the other functions, the VABC algorithm is much better than the ABC algorithm. The VABC algorithm can increase the mean and the standard deviation of the functions by almost two orders of magnitude than ABC algorithm.

In order to show the performance of the VABC algorithm more clearly, the graphical representations of the results in Table 2 are reproduced in Figures 2-7. For economy of space, just parts of graphics are presented. From the figures, we are concluded that the speed of convergence of VABC is much faster than ABC algorithm on all functions. From Figure 4 and Figure 7, we can observe that the ABC algorithm is easy trapped at loacl optimum and the VABC algorithm is able to continue improving its solution on these two functions.

TABLE II. RESULTS COMPARISON OF DIFFERENT OPTIMAL ALGORITHMS FOR 30 RUNS

30D		ABC	VABC
f_1	Mean	1.1396e-014	**6.7374e-016**
	Std	8.0826e-015	**9.4347e-017**
f_2	Mean	3.3325e-001	**1.7060e-001**
	Std	2.3784e-001	**1.7242e-001**
f_3	Mean	6.0208e-007	**1.0191e-008**
	Std	3.2419e-006	**5.3151e-008**
f_4	Mean	1.8603e-001	**9.1437e-007**
	Std	3.6710e-001	**4.8177e-006**
f_5	Mean	6.0643e-006	**4.1871e-008**
	Std	3.5254e-006	**1.6534e-008**
f_6	Mean	1.9897e+002	**9.4874e+001**
	Std	1.1697e+002	**8.4636e+001**
f_7	Mean	4.4656e-004	**2.5574e-005**
	Std	1.1370e-004	**5.4065e-006**
f_8	Mean	3.2510e-001	**9.8423e-008**
	Std	5.3353e-001	**3.3229e-007**
f_9	Mean	6.8561e-013	**8.8469e-016**
	Std	8.6194e-013	**1.6481e-016**
f_{10}	Mean	4.6798e-007	**4.2875e-009**
	Std	1.7600e-007	**1.8939e-009**
f_{11}	Mean	1.3222e-002	**4.7439e-003**
	Std	6.0301e-003	**6.6657e-003**

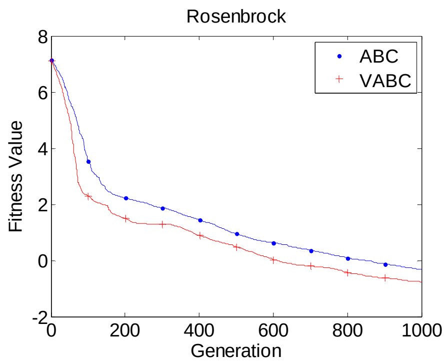

Fig.2. The median convergence characteristics of Rosenbrock function.

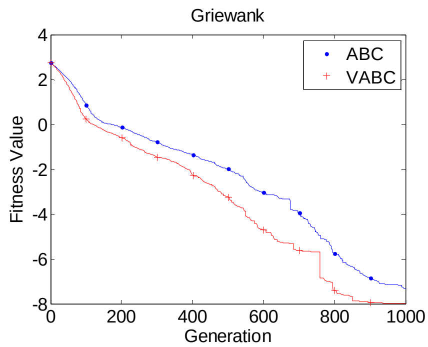

Fig.3. The median convergence characteristics of Griewank function.

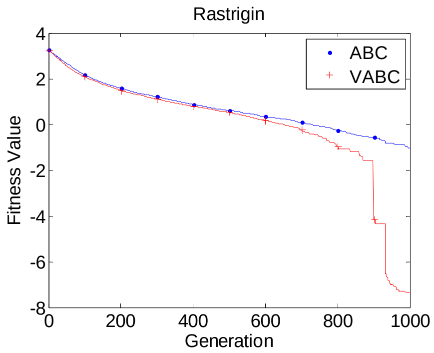

Fig.4. The median convergence characteristics of Rastrigin function.

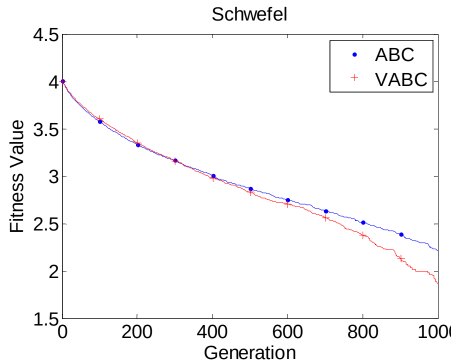

Fig.5. The median convergence characteristics of Schwefel function.

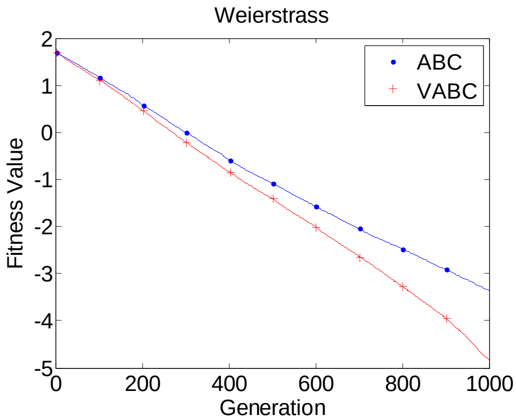

Fig.6. The median convergence characteristics of Weierstrass function.

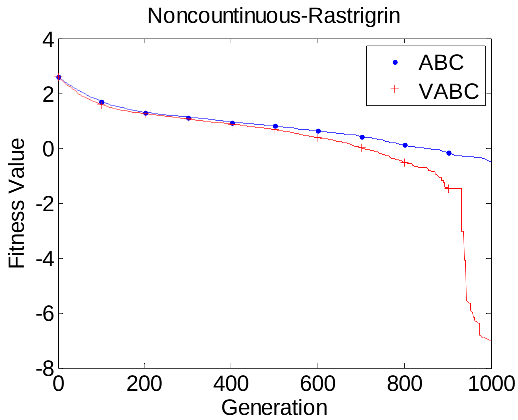

Fig.7. The median convergence characteristics of Noncountinuous-Rastrigrin function.

5. Conclusion

This paper, based on the Von Neumann topology structure, a novel Article Bee Colony (ABC) algorithm is presented, namely Von Neumann Neighborhood Article Bee Colony (VABC). This resulted in a significant improvement in the performance in terms of solution quality, convergence speed and robustness.

In order to demonstrate the performance of the VABC algorithm, we compared the performance of the VABC with those of ABC algorithm on a set of benchmark functions. From the simulation results, it is concluded that the proposed algorithm has the ability to attain the global optimum and get rid of local minima, moreover it definitely outperforms the original ABC.

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