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Labor Division Artificial Bee Colony Algorithm for Numerical Function Optimization

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Abstract

Swarm intelligence is briefly defined as the collective behavior of decentralized and self-organized swarms. Self-organization and labor division are the two key components of swarm intelligence. Artificial Bee Colony (ABC) algorithm is one of the most recent swarm intelligence-based algorithms. The behavior of bees in ABC algorithm satisfies the self-organization features, but there is no specific labor division mechanism in ABC algorithm. In this work, we propose an improved ABC algorithm called labor division artificial bee colony (LDABC) algorithm by incorporating the labor division mechanism into ABC algorithm, which is achieved by individual specialization and role plasticity. We specify three different search methods for employed bees, onlooker bees and scout bees to realize individual specialization, these search methods are related to food source quality, enable bees to maximize exploitation of food source. Role plasticity is achieved by combining with cellular automata, where the roles of bees are not static but vary with their surrounding environment, enable bees not to limit to one search method. The different search modes and the flexibility of the search behaviors make our algorithm achieve a better balance between exploration and exploitation. The experimental results tested on 13 benchmark functions and CEC-2013 test functions demonstrate a competitive performance.

Keywords

Swarm Intelligence; Self-Organization; Labor Division; Artificial Bee Colony; Numerical Optimization

Introduction

Artificial Bee Colony (ABC) algorithm proposed by Karaboga [1] in 2005 is a biological-inspired optimization algorithm based on the foraging behavior of honey bee swarm. It has been successfully used for numerical optimization problems, and the experimental results [2-4] showed that ABC is competitive with other optimization methods such as genetic algorithm (GA), particle swarm optimization (PSO) and differential evolution (DE) algorithm. Besides numerical optimization, ABC is also applied to solve many practical optimization problems such as filter modeling [5], clustering analysis [6], and image registration [7].Similar to other optimization algorithms, ABC also has some disadvantages such as slow convergence speed when solving unimodal problems and easily getting trapped in the local optima when handling complex multimodal problems [4].For the shortcomings of ABC algorithm, some researchers modified the solution search equation to improve its performance, for example Tsai et al. [8] introduced the concept of universal gravitation into the consideration of the affection between the employed bees and the onlooker bees to maximize the exploitation capacity (Interactive ABC). Akay and Karaboga [9] introduced two parameters perturbation frequency and magnitude of the perturbation into the solution search equation of the basic ABC to improve the convergence rate. Inspired by PSO, Zhu and Kwong [10] proposed an improved ABC algorithm called Gbest-guided ABC (GABC) algorithm by incorporating the information of global best solution into the solution search equation. Gao and Liu [11,12] proposed an improved/modified ABC algorithm by adding the mutation operation of differential evolution algorithm to the solution search equation. Li et al. [13] introduced the best-so-far solution, inertia weight and acceleration coefficients to the solution search equation to improve the convergence speed. The modification of the solution search equation in all above methods made the improved ABC algorithm achieve a better balance between exploration and exploitation.

Bonabeau has defined the swarm intelligence as “any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies” [14]. Swarm intelligence-based algorithms include Ant Colony Optimization (ACO) [15], Particle Swarm Optimization (PSO) [16], Artificial Bee Colony Algorithm (ABC) [1], and soon. Self-organization and labor division are the two key properties of swarm intelligence. Self-organization is a process whereby pattern and structure at the global level of a system emerges solely from numerous interactions among the lower-level components of the system. Moreover, the rules specifying interactions among the system’s components are executed using only local information, and neither global information nor centralized control is needed [17]. An obvious feature of labor division is its plasticity, which is caused by the flexibility of individual behaviors, that is the proportion of individual simple menting different tasks can be changed under the inside pressure of reproduction and external influence of aggressive challenges [18].

The foraging behavior of honey bees satisfies the four features of self-organization: positive feedback, negative feedback, fluctuations and multiple interactions. ABC algorithm based on the foraging behavior of honey bees also describes the four characteristics [1], but there is no specific labor division mechanism in ABC algorithm. We take this as a breakthrough point and propose the Labor Division Artificial Bee Colony (LDABC) algorithm by integrating labor division mechanism into ABC algorithm. Here labor division is achieved by individual

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specialization and role plasticity. We customize three different search modes for employed bees, onlooker bees and scout bees to realize individual specialization, and role plasticity is achieved by combining with cellular automata, where the role of the bees is determined by its surrounding environment. In the labor division mechanism, bees adopt different search modes according to the role, at the same time; the role is not static but varies with environment. The different search modes and the flexibility of the search behaviors make our algorithm achieve a better balance between exploration and exploitation, and then improve the searching efficiency.

Artificial Bee Colony Algorithm

The artificial bee colony (ABC) [1] algorithm model contains three kinds of bees: employed bees, onlooker bees and scout bees. The population is divided into half-and-half employed bees and onlooker bees. Employed bees search for a new food source near the food source in their memory, and share the information with a probability proportional to the nectar amounts (profitability) of the food source. Onlooker bees select a food source based on the shared information and search around the selected food source. Employed bees abandon the food source due to its depletion and become scout bees searching for a new food source. The location of the food source corresponds to a feasible solution of the optimization problem, and the profitability of the food source represents the solution quality (fitness). The number of employed bees is equal to the number of food sources. In other words, there is only one employed bee foraging the nectar in each food source.

In ABC, the initialization of the food source of employed bees can be obtained by the following expression (1):

$$x_{ij} = x_j^{\min} + \mathrm{rand}\left(0,1\right)(x_j^{\max} ?\ x_j^{\min}) \qquad (1)$$

Where i=1,…,SN, j=1,…,D.SN represents the number of the food sources. D is the dimension of the optimization problem. x_j^{min} is the lower bound of the food source position in dimension j and x_j^{max} is the upper bound of the food source position in dimension j.

Employed bees forage a new food source via round the food source x_i^{in} their memory, which is shown as the following expression (2):

$$v_{ij} = x_{ij} + f_{ij}\ \left(x_{ij} - x_{kj}\right) \qquad (2)$$

Where j∈[1,D] and k∈[1,SN] are random generating indexes, but k must be different from i. ϕ_{ij} is a random number between [-1,1].The greedy selection is adopted for xi and vi. If the new food source via cannot be improved further than previous food source xi through a predetermined number of parameter called "limit", the food source x_i should be abandoned. Then the corresponding employed bee converts into scout bee to find a new food source by means of Eq. (1).

An onlooker bee selects a food source depending on roulette wheel selection scheme. The higher the profitability of the food source is, the bigger the probability that it can be selected. The probability p_i of the food source can be defined as follows:

$$p_t = \frac{fitness_t}{\sum_{e=1}^{SN} fitness_t} \qquad (3)$$

Onlooker bees like employed bees search a new food source via round the selected food source x_i, and also apply the greedy selection to update the food source. The difference is that all of the food sources are likely to be updated in the search of employed bees, but for onlooker bees only selected food source could be updated.

The foraging behavior of honey bees meets the four features of self-organization, and ABC algorithm based on the foraging behavior of honey bees also describes these four characteristics [1]: i) Positive feedback: the number of onlooker bees visiting the food source is proportional to the profitability of food source. ii) Negative feedback: the food source is abandoned when it cannot be improved through a number of "limit". iii) Fluctuations: scout bees carry out a random search process for discovering new food sources. iv) Multiple interactions: employed bees share their information about food sources with onlooker bees.

Labor division artificial bee colony algorithm

Self-organization and labor division are the two key properties of swarm intelligence, and they are necessary and sufficient properties to obtain swarm intelligent behaviors. As mentioned above, self-organization exists in ABC algorithm, but there is no specific labor division mechanism in ABC algorithm. Labor division is fundamental to the organization of insect societies and is thought to be one of the principal factors in their ecological success [18]. A key feature of labor division in insect colonies is its plasticity. Colonies respond to changing internal and external conditions by adjusting the ratios of individual workers engaged in the various tasks. This is accomplished by the behavioral flexibility of individual workers, which can be characterized by individual specialization and role plasticity [19]. Individual specialization refers to the individual preference for different tasks, this preference varies with size, age, dominance order, and so on. Role plasticity means role conversion caused by environmental background and task priority, individual can easily switch task. In addition, individual also has the ability to learn, which promotes individual specialization in a certain extent. The result is through mutual cooperation the group achieves effective task allocation and survives in complicated environment. Research on labor division bases on the biological background, we simulate the behavior of honey bee swarm from self-organization and labor division by integrating labor division mechanism into ABC algorithm.

Here the labor division mechanism mainly consists of individual specialization and role plasticity. Individual specialization makes bees adopt different search modes, role plasticity enables bees be ready to convert from one character to another according to the change of surrounding environment, i.e. convert from one search mode to another (Figure 5).

Individual specialization

There are three kinds of bees in ABC algorithm: employed bees, onlooker bees and scout bees, where

urces. Different flight patterns represent work in different ways, and reflect the different tasks. Individual preference for different tasks is determined by the profitability of food sources exploited by the individual bees. Bees with higher profitability of food sources are defined as employed bees, scout bees are associated with lower profitability of food sources, the remaining bees are onlooker bees. Flight patterns relate to information utilized by the bees, where employed bees and scout bees can perceive the whole swarm information, onlooker bees can only sense the information in its neighborhood. Here the neighborhood refers to a kind of population structure, in which bees have fixed positions, positions adjacent to a bee according some rules is called the neighborhood of that bee, the specific definition of neighborhood will be discussed in next section. Three kinds of bees with three flight modes could rich dynamic behaviors of bee swarm, and also effectively avoid the premature convergence. These three flight modes are described as follows.

The flight mode for employed bees to search food sources is depicted as the following expression (4):

$$v_{ij} = x_{ij} + f_{ij} \left(x_{ij} - x_{kj}\right) + y_{ij} \left(x_{gj} - x_{ij}\right) \quad (4)$$

where $\phi_{ij}\in[-1,1]$, $\psi_{ij}\in[0,C1]$, C1>0, $j\in\{1,2,\ldots,D\}$. Employed bees can perceive the whole swarm information, xi is the employed bee's food source in its memory, x_k is another employed bee's food source in the neighborhood of current employed bee, and x_g is the best food source of bee swarm at present. Eq. (4) is obtained by adding ψ_{ij} $(x_{gj}-x_{kj}$) to Eq. (2). In original ABC algorithm, new food source v_i is generated by the perturbation on old food source x_i measured by the difference between x_i and x_k, where x_k is randomly selected. The probability of random selection to good food source is the same with that of random selection to poor food source, so the new candidate food source is not promising to be better than the previous one. The third term in the right-hand side of Eq. (4) can drive the new candidate food source towards the global best one, which makes the search more directional. Once the candidate food source is obtained, it will be compared with the old one, and a greedy selection mechanism is employed between them.

Onlooker bees adopt Eq. (5) as the flight mode to search food sources:

$$v_{ij} = x_{ij} + f_{ij} \left(x_{ij} - x_{kj}\right) + y_{ij} \left(x_{pj} - x_{ij}\right) \quad (5)$$

where $\phi_{ij}\in[-1,1]$, $\psi_{ij}\in[0,C2]$, C2>0, $j\in\{1,2,\ldots,D\}$. Eq. (5) has the same form with Eq. (4), but the meaning of each part is different. Here onlooker bees can only sense the information in its neighborhood, x_i is the onlooker bee's food source in memory, x_k is a selected employed bee's food source in the neighborhood of current onlooker bee, and x_p is the best food source in the neighborhood. A greedy selection mechanism is employed between x_i and v_i. The third term in the right-hand side of Eq. (5) can drive the search of onlooker bees towards the best food source in its neighborhood. In original ABC algorithm, onlooker bees choose employed bees' food sources by a roulette wheel selection based on profitability of the food source. Due to a limited number of employed bees in a neighborhood, the probability that x_p is selected is biggest, and the probability that x_k is same with x_p is also increased, which is not beneficial to search. Here we select x_k by a roulette wheel selection shown as Eq. (6) based on the distance between food sources.

$$P_k = \frac{1}{dis(x_i,x_k)} \bigg/ \sum_{j=1}^{n} \frac{1}{dis(x_i,x_j)} \quad (6)$$

Where d is (x_i,x_j) is the Euclidean distance between food source x_i and x_j, n denotes the number of employed bees in neighborhood. The closer the distance d is (x_i, x_j) is, the higher probability that food source x_j is selected. So it can reduce the probability that x_k is same with x_p, and increase the search around x_i as well as population diversity.

The following expression (7) is defined as scout bees' flight mode to search food sources:

$$v_{ij} = x_{ij} + F_{ij} \left(x_{pj} - x_{ij}\right) + j_{ij} \left(x_{gj} - x_{ij}\right) \quad (7)$$

where $\Phi_{ij}\in[0,C3]$, C3>0,$\varphi_{ij}\in[0,C4]$, C4>0, $j\in\{1,2,\ldots,D\}$. Scout bees can perceive the whole swarm information, x_i is the scout bee's food source in its memory, x_p is the best food [source in its neighborhood, and x_g is the best food source of current bee swarm. Scout bees are associated with lower profitability of food sources, search towards x_p and x_g can greatly improve its food source. Greedy selection mechanism is also employed between x_i and v_i.

Three different flight modes could rich dynamic behaviors of bee swarm, and also improve search efficiency. The characteristics of the three kinds of bees are summarized in Table 1.

x_g is the best food source in the bee swarm, x_p is the best food source in the neighborhood

Role plasticity

The prerequisite for the success of insect society is individual worker's ability to switch tasks quickly and accurately. Their roles can vary to adapt to dynamically changing environmental conditions, which means capable of plasticity. A non-social insect, such as a solitary wasp, when dealing with a task, it has no choice but to take the task as an uninterrupted series of steps to perform (Figure 1a). But a group is able to perform multiple such tasks simultaneously in a parallel series way (Figure 1b). If individual worker can quickly and flexibly switch to its closest tasks or tasks stopped by other workers, the entire process will undoubtedly be accelerated, which does exist in insect society, and it is a series parallel process (Figure 1c).

There exists mutual transformation among employed bees, onlooker bees and scout bees in the original ABC algorithm, and this kind of transformation is based on food source quality. Employed bees with higher profitability of food sources recruit onlooker bees to update their food sources. If the new food source is updated by employed bee, then employed bee and corresponding onlooker bees keep the original role unchanged; if the new food source is updated by an onlooker bee, then this onlooker bee transforms into employed bee and the original employed bee transforms into onlooker bee with the rest onlooker bees stay unchanged. Employed bees with lower food source may not recruit onlooker bees and update food sources alone, their roles keep unchanged. But if employed bee's food source doesn't get update in continuous "limit" time, it transforms into scout bee and randomly searches food source. From the above analysis, the frequency of transformation between employed bees and onlooker

Bees	Corresponding food source	Perception range	Search direction
Employed bees	High profitability	The whole bee swarm	Towards x_g
Onlooker bees	Middle profitability	In the neighborhoodT	Towards x_p
Scout bees	Low profitability	The whole bee swarm	Towards x_p and x_g

Table 1: Characteristics of three kinds of bees.

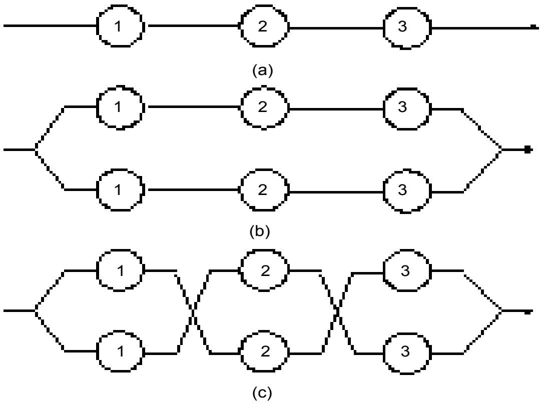


Figure 1: Different ways of performing tasks.

bees is relatively high, but their search modes are the same and there is no difference essentially. Employed bee's search mode is different from scout bee, but their transformation condition is rigorous, so the frequency is very low. Therefore, although there is role transformation in ABC algorithm, it's not obvious.

Here, through a combination with cellular automata to realize role plasticity. Cellular automata is a spatially and temporally discrete model [20,21]. It is composed of a finite set of cells on a grid, each in one of a finite number of states. The grid can be in any finite number of dimensions, in two dimensions, square, triangular, and hexagonal grids may be considered. For each cell, usually a set of cells directly adjacent to it are called its neighborhood. The update of a cell state is determined by the current state of the cell and the states of the cells in its neighborhood. Two common neighborhoods in the case of two-dimensional cellular automata are Moore neighborhood (a square neighborhood) and von Neumann neighborhood (a diamond-shaped neighborhood). Take Moore neighborhood as an example to explain the concept of neighborhood (Figure 2), in a 5×5 square grid, each circle represents a cell, a cell's upper, lower, left, right, upper left, lower left, upper right, lower right adjacent eight cells are neighbors of that cell, these neighbors compose the Moore neighborhood of that cell. In Figure 2, the grey cells are the Moore neighborhood of the black cell.

Corresponding to our labor division artificial bee colony algorithm, bees can be seen as cells and there are three states: employed bees, onlooker bees and scout bees. Define a population structure as the grid, each bee in the population has a fixed position, and Moore neighborhood is applied. In each neighborhood, bees with high quality food sources are defined as employed bees, bees with low quality food sources are defined as scout bees, the rest bees are defined as onlooker bees. In other words, the state of each bee is determined by the current state of the bee and the states of bees in its neighborhood. Based on these settings, the role of bees can vary with the change of the surrounding environment: (1) the proportion of three kinds of bees remains stable in neighborhood, different kinds of bees have different perception range and search mode. Each search mode has a certain degree of randomness, which leads to different update speed of food sources, so that the bees are not limited to the same role; (2) the overlaps of neighborhoods between adjacent bees may make bees play a certain role in one neighborhood, and another role in another neighborhood. As the proportion of role maintains a balance in neighborhood, it also affects the role of other bees; (3) the search modes of these three kinds of bees all associate with employed bees' food sources, and in turn the change of the role affects the updates of food sources.

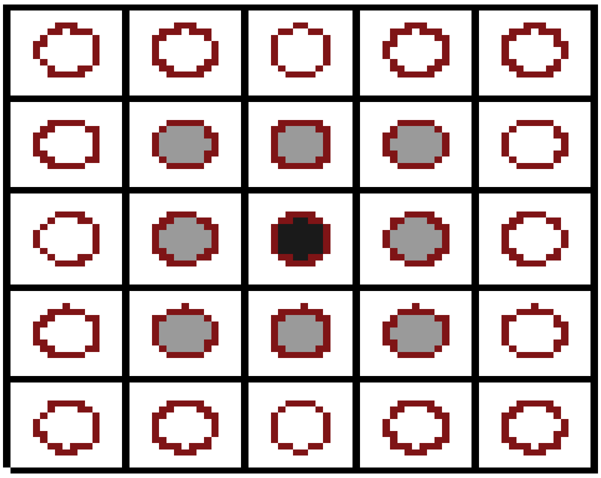
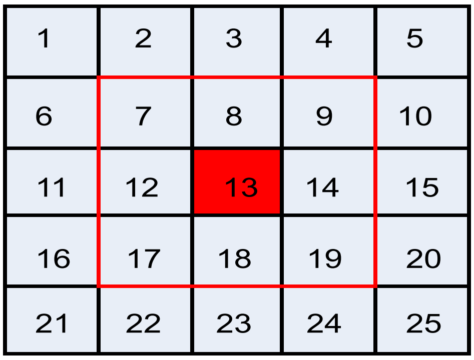


Figure 2: Moore neighborhood.

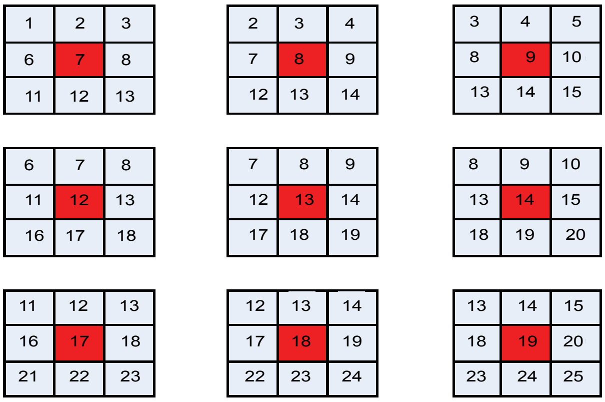
Furthermore, the overlaps of neighborhoods between adjacent bees will make the information about high-quality food source slowly spread in the population. Assume that the population size is 25 with a 5×5 square population shape, where the 25 individuals have fixed position as shown in Figure 3. Moore neighborhood is adopted. The state of individual 13 is determined by its neighbors 7,8,9,12,14,17,18,19, and the states of individual 7, 8, 9, 12, 14, 17, 18, 19 are determined by their respective neighbors, as shown in Figure 4. Table 2 gives the differences among neighbors of individual 7,8,9,12,14,17,18,19. There are average five different individuals between these neighbors, i.e. more than half of the neighbors are different (each individual has eight neighbors). The result is that the same neighbors make good individuals not be lost, different neighbors makes good individuals slowly spread in the population, which avoids a rapid fall into local optimum and be able to take the diversity and efficiency into account. The neighborhood decides how many individuals it contains and controls the speed of information dissemination as well as the loss of information. The more individuals in the neighborhood, the faster information dissemination, and then algorithm may easily converge to the early optimal solution; on the contrary, if there is a small number of individuals in the neighborhood, good solution information can't spread in the population timely, resulting in a slow rate of convergence.

At last, in original ABC algorithm, bees use fixed order to update food sources: First employed bees update their food sources, and then



1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

Figure 3: Population shape with square grid.



1	2	3
6	7	8
11	12	13

2	3	4
7	8	9
12	13	14

3	4	5
8	9	10
13	14	15

6	7	8
11	12	13
16	17	18

7	8	9
12	13	14
17	18	19

8	9	10
13	14	15
18	19	20

11	12	13
16	17	18
21	22	23

12	13	14
17	18	19
22	23	24

13	14	15
18	19	20
23	24	25

Figure 4: Individual and its neighbors.

onlooker bees choose an employed bee and update corresponding food sources. Here, we adopt a different update order described as follows: generate a random sequence of 1 to n at regular iteration intervals, then update food sources according to this random sequence, where n is the number of food sources. Due to the information exchange among bees, the update order to some extent affects the update of food sources, and then influences the role of bees. The random sequence increases uncertainty to the update of food sources as well as role exchange, which enhances role plasticity.

	7	8	9	12	14	17	18	19
7	0	3	6	3	7	6	7	8
8	3	0	3	5	5	7	6	7
9	6	3	0	7	3	8	7	6
12	3	5	7	0	6	3	5	7
14	7	5	3	3	0	7	5	3
17	6	7	8	3	7	0	3	6
18	7	6	7	5	5	3	0	3
19	8	7	6	7	3	6	3	0
sum	40	36	40	33	36	40	36	40
mean	5.714	5.1429	5.714	4.714	5.143	5.714	5.143	5.714

Table 2: Differences among neighbors of adjacent individuals.

Implementation Process of Labor Division Artificial Bee Colony Algorithm

Experiments

Test functions: In this section, LDABC algorithm is applied to minimize a set of 13 benchmark functions as shown in Table 3. Specifically, functions f1-f6 are unimodal functions; function f7 is a noisy quartic function; functions f8-f13 are multimodal functions and the number of local minima increases exponentially with the problem dimension.

Further, we evaluate the performance of LDABC algorithm by solving the set of problems introduced in the CEC-2013 Special Session on Real-Parameter Optimization [22], which are grouped into three categories: uni-modal functions, multi-modal functions and composition functions. Here we choose Sphere Function, Rotated High Conditioned Elliptic Function, Rotated Rosenbrock's Function, Rotated Schaffers F7 Function, Composition Function 1 and Composition Function 2 to test.

Parameter settings: The performance of improved ABC algorithm is obviously better than that of the original ABC algorithm. In order to evaluate the performance of LDABC algorithm, we compare with several improved ABC algorithm, such as CABC [23], GABC [10],

Function name	Function	Characteristic	Ranges	Min
Sphere	$f_1(x)=\sum_{i=1}^{D} x_i^2$	Unimodal	[-100,100]	0
Schwefel 2.22	$f_2(x)=\sum_{i=1}^{D}\lvert x_i\rvert+\prod_{i=1}^{D}\lvert x_i\rvert$	Unimodal	[-10,10]	0
Schwefel 1.2	$f_3(x)=\sum_{i=1}^{D}\left(\sum_{i=1}^{D} x_i\right)^2$	Unimodal	[-100,100]	0
Schwefel 2.21	$f_4(x)=\max_i\{\lVert x_i\rVert, 1\le i\le D\}$	Unimodal	[-100,100]	0
Rosenbrock	$f_5(x)=\sum_{i=1}^{D\text{-}1}[100(x_{i+1}-x_i^2)^2+(1-x_i)^2]$	Unimodal	[-30,30]	0
Step	$f_6(x)=\sum_{i=1}^{D}(\lfloor x_i+0.5\rfloor)^2$	Unimodal	[-100,100]	0
Quartic	$f_7(x)=\sum_{i=1}^{D} ix_i^4+random(0,1)$	Unimodal	[-1.28,1.28]	0
Schwefel	$f_8(x)=\sum_{i=1}^{D}-x_i\sin(\sqrt{\lVert x_i\rVert})+418.98288727243369D$	Multimodal	[-500,500]	0
Rastrigin	$f_9(x)=\sum_{i=1}^{D}(x_i^2-10\cos(2\pi x_i)+10)$	Multimodal	[-5.12,5.12]	0
Ackley	$f_{10}(x)=-20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2})$ $-\exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i))+20+e$	Multimodal	[-32,32]	0
Griewank	$f_{11}(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}})+1$	Multimodal	[-600,600]	0
Penalized	$f_{12}(x)=\frac{\pi}{D}\{10\sin^2(\pi y_1)+\sum_{i=1}^{D\text{-}1}(y_i-1)^2[1+10\sin^2(\pi y_{i+1})]$ $+(y_D-1)^2\}+\sum_{i=1}^{D}u(x_i,10,100,4)$	Multimodal	[-50,50]	0

Table 3: Benchmark functions used in experiments.

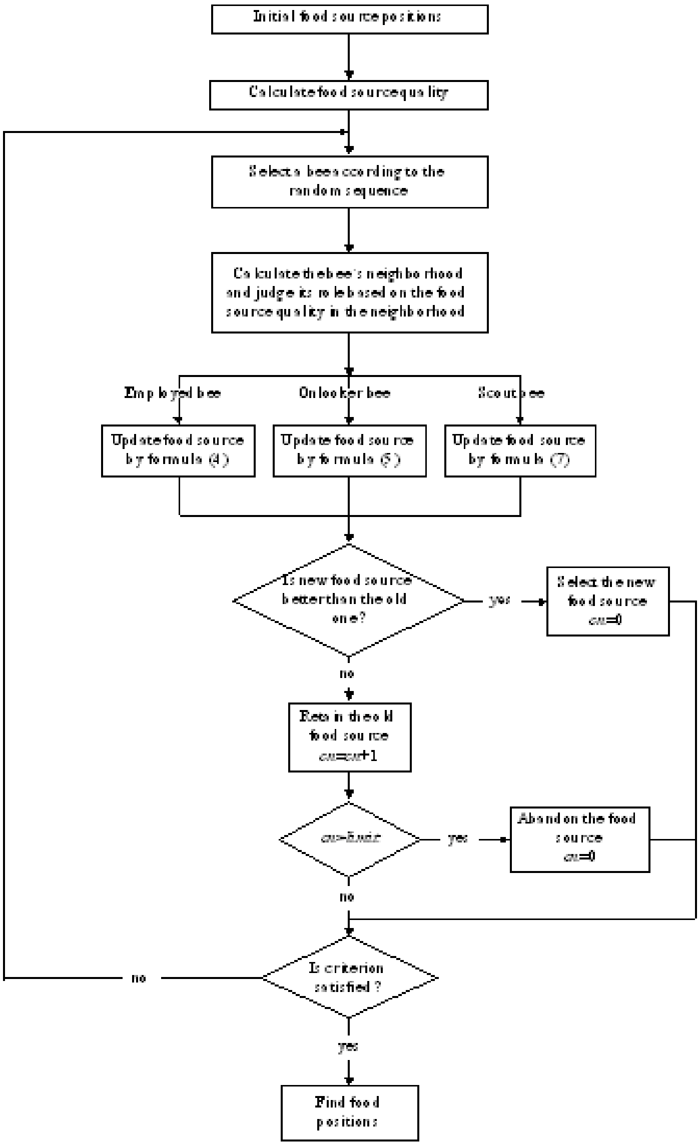

Initial food source positions
Calculate food source quality
Select a bee according to the random sequence
Calculate the bee's neighborhood and judge its role based on the food source quality in the neighborhood
Employed bee
Onlooker bee
Scout bee
Update food source by formula (4)
Update food source by formula (5)
Update food source by formula (7)
Is new food source better than the old one?
yes
Select the new food source cnt=0
no
Retain the old food source cnt=cnt+1
cnt=limit
yes
Abandon the food source cnt=0
no
Is criterion satisfied ?
no
yes
Find food positions

Figure 5: Implementation process of LDCABC algorithm.

RABC [24], IABC [11] on 13 benchmark functions, where IABC has been compared with CABC, GABC and RABC. To ensure the accuracy of the comparison, we follow the parameter settings in the original paper of IABC, and the results are gained form [11] directly. IABC has also compared with three variants of DE: SaDE [25], jDE [26], JADE [27], we compare with them too. Every experiment is repeated 30 times independently.

For CEC-2013 test functions, the algorithm was run 51times for each test problem, where the stopping criterion was to run for up to 1000D function evaluations (FEs), where D is 10, 30 and 50 variables.

The population size of LDABC is 36 with a 6×6 square population shape, Moore neighborhood is applied, the role ratio of three kinds of bees in neighborhood is 1:1:1, the value of C1 and C2 are set to 1.5, the value of C3 and C4 are fixed to 1.32.

Results and discussion

For the 13 benchmark functions, the experiment results are shown in Tables 4 and 5, where the best results are marked in bold. As seen from Tables 4-5, the LDABC found the theoretical global optima on 6 functions (f6, f8, f9, f11, f12 and f13), except for the function f8 and f9 under function evaluations (FEs)=50000. Especially, the global minimal value of function f6 was found under FEs=7000. The results of LDABC were extremely close to the theoretical optima on 4 functions (f1, f2, f3 and f4). On functions f5, f7 and f10, the LDABC could achieve the solutions close to the global optima.

Compared with SaDE, jDE and JADE, LDABC performed much better than these DE variants on almost all the functions, while JADE performs a little better than LDABC on function f7. Compared with ABC variants, LDABC was superior to CABC on all functions; LDABC outperformed GABC and IABC except for functions f8 and f9; RABC performs better than LDABC only on functions f5 and f8, and it finds the best solution on function f5. So it is concluded that LDABC is much more effective.

In the experiment, we have found that LDABC achieved the global

Fun	Fes		SaDE	jDE	JADE	LDABC
f1	1.5×105	Mean	4.5e-20	2.5e-28	1.8e-60	3.49e-195
		St.d	1.9e-14	3.5e-28	8.4e-60	0
f2	2.0×105	Mean	1.9e-14	1.5e-23	1.8e-25	2.88e-143
		St.d	1.1e-14	1.0e-23	8.8e-25	1.12e-142
f3	5.0×105	Mean	9.0e-37	5.2e-14	5.7e-61	9.78e-79
		St.d	5.4e-36	1.1e-13	2.7e-60	2.53e-78
f4	5.0×105	Mean	7.4e-11	1.4e-15	8.2e-24	6.90e-44
		St.d	1.82e-10	1.0e-15	4.0e-23	9.68e-44
f5	2.0×106	Mean	1.8e+01	8.0e-02	8.0e-02	8.90e-06
		St.d	6.7e+00	5.6e-01	4.0e-23	1.55e-05
f6	1.0×104	Mean	9.3e+02	1.0e+03	2.9e+00	0
		St.d	1.8e+02	2.2e+02	1.2e+00	0
f7	3.0×105	Mean	4.8e-03	3.3e-03	6.4e-04	1.03e-03
		St.d	1.2e-03	8.5e-04	2.5e-04	2.81e-04
f8	1.0×105	Mean	4.7e+00	7.9e-11	3.3e-05	0
		St.d	3.3e+01	1.3e-10	2.3e-05	0
f9	1.0×105	Mean	1.2e-03	1.5e-04	1.0e-04	0
		St.d	6.5e-04	2.0e-04	6.0e-05	0
f10	5.0×104	Mean	2.7e-03	3.5e-04	8.2e-10	7.10e-15
		St.d	5.1e-04	1.0e-04	6.9e-10	0
f11	5.0×104	Mean	7.8e-04	1.9e-05	9.9e-08	0
		St.d	1.2e-03	5.8e-05	6.0e-07	0
f12	5.0×104	Mean	1.9e-05	1.6e-07	4.6e-17	0
		St.d	9.2e-06	1.5e-07	1.9e-16	0
f13	5.0×104	Mean	6.1e-05	1.5e-06	2.0e-16	0
		St.d	2.0e-05	9.8e-07	6.5e-16	0

Table 4: Performance comparisons of LDABC, SaDE, jDE and JADE.

optimum on function f6 with the least function evaluations of 7000; for function f8 and f9 LDABC found the worse solutions compared with other ABC variants under FEs=50000, but it could find the global optima with function evaluations of 80000. This suggests that LDABC is convergent but with different convergence speed, which may be caused by the step size. There are four parameters C1, C2, C3 and C4 controlling the step size towards x_p and x_g, which are constants in the experiment.

For CEC-2013 test functions, the experiment results are shown in Table 6. For uni-modal functions Sphere Function and Rotated High Conditioned Elliptic Function, LDABC achieved the best solutions; For multi-modal functions Rotated Rosenbrock's Function and Rotated Schaffers F7 Function, LDABC found the better solutions; For composition functions Composition Function 1 and Composition Function 2, LDABC got the worst solutions. This may also be caused by the step size.

Conclusion

Self-organization and labor division are the two key components of swarm intelligence, and they are necessary and sufficient properties to obtain swarm intelligent behaviors. In social insect colonies, each of the individual may respond to local stimuli and act together to accomplish a global task via labor division without a centralized supervision. The behavior of bees in ABC algorithm satisfies the four features of self-organization, but there is no specific labor division mechanism in ABC algorithm. In this work, we incorporate the labor division mechanism into ABC algorithm, which is achieved by individual specialization and role plasticity.

Individual specialization means individual preference for different tasks, as well as different ways of working. We imitate it by specifying three different search methods for employed bees, onlooker bees and scout bees to rich forage behaviors of bees. These search methods relate to food source quality, enable bees to maximize exploitation of food source. Role plasticity refers to the flexibility of individual behaviors, individuals can switch tasks through role exchange to adapt to dynamic changes in the environment. Role plasticity is achieved by combining with cellular automata, where the roles of bees are not static but vary with their surrounding environment, which enables bees not to limit to one search method. In addition, the neighborhood in cellular automata is also introduced. The overlaps of neighborhoods between adjacent bees will make the information about high-quality food source slowly spread in the population, leading to good information never lost nor quickly occupy the whole space. In other words, it could control the speed of information dissemination and information loss. After that a random update order to update food sources is adopted to enhance role plasticity. The different search modes and the flexibility of the search behaviors make our algorithm achieve a better balance between exploration and exploitation. The experimental results tested on 13 benchmark functions and CEC-2013 test functions demonstrate a competitive performance.

Some valuable work in the future includes the study on the

Fun	Fes		CABC	GABC	RABC	IABC	LDABC
f1	1.5×105	Mean	2.3e-40	3.6e-63	9.1e-61	5.34e-178	3.49e-195
		St.d	1.7e-40	5.7e-63	2.1e-60	0	0
f2	2.0×105	Mean	3.5e-30	4.8e-45	3.2e-74	8.82e-127	2.88e-143
		St.d	4.8e-30	1.4e-45	2.0e-73	3.49e-126	1.12e-142
f3	5.0×105	Mean	8.4e+02	4.3e+02	2.9e-24	1.78e-65	9.78e-79
		St.d	9.1e+02	8.0e+02	1.5e-23	2.21e-65	2.53e-78
f4	5.0×105	Mean	6.1e-03	3.6e-06	2.8e-02	4.98e-38	6.90e-44
		St.d	5.7e-03	7.6e-07	1.7e-02	8.59e-38	9.68e-44
f5	2.0×106	Mean	2.1e-02	6.7e-03	6.4e-23	4.75e-03	8.90e-06
		St.d	3.5e-02	8.6e-02	3.8e-22	4.22e-02	1.55e-05
f6	1.5×105	Mean	0	0	0	0	0
		St.d	0	0	0	0	0
f7	3.0×105	Mean	3.8e-02	1.1e-02	3.6e-02	2.42e-03	1.03e-03
		St.d	5.2e-01	5.3e-02	6.8e-03	5.57e-04	2.81e-04
f8	5.0×104	Mean	5.3e+02	9.7e+01	9.2e-02	0	1.57e+02
		St.d	4.8e+02	9.2e+01	1.5e-02	0	1.08e+02
f9	5.0×104	Mean	1.3e-00	1.5e-10	2.3e-02	0	1.55e-05
		St.d	2.7e-00	2.7e-10	5.1e-01	0	1.48e-05
f10	5.0×104	Mean	1.0e-05	1.8e-09	9.6e-07	3.87e-14	7.10e-15
		St.d	2.4e-06	7.7e-10	8.3e-07	8.52e-15	0
f11	5.0×104	Mean	1.2e-04	6.0e-13	8.7e-08	0	0
		St.d	4.6e-04	7.7e-13	2.1e-08	0	0
f12	5.0×104	Mean	4.2e-11	8.5e-20	5.4e-16	1.57e-32	0
		St.d	5.3e-11	4.1e-20	2.8e-16	2.73e-48	0
f13	5.0×104	Mean	7.4e-09	5.3e-18	1.5e-12	1.35e-32	0
		St.d	8.1e-09	4.8e-18	2.7e-12	2.73e-48	0

Table 5: Performance comparisons of LDABC, CABC, GABC, RABC and IABC.

Fun	Dim	Best	Worst	Median	Mean	Std
Sphere Function	10	1.0e-08	1.0e-08	1.0e-08	1.0e-08	0
Rotated High Conditioned Elliptic Function		1.0e-08	1.0e-08	1.0e-08	1.0e-08	0
Rotated Rosenbrock’s Function		1.0e-08	1.0e-08	1.0e-08	1.0e-08	0
Rotated Schaffers F7 Function		1.0e-08	5.1e-05	2.5e-07	3.3e-06	1.4e-05
Composition Function 1		1.0e+02	2.8e+02	2.0e+02	2.1e+02	1.1e+01
Composition Function 2		4.8e+00	1.3e+02	1.0e+02	7.6e+01	2.1e+01
Sphere Function	30	1.0e-08	1.0e-08	1.0e-08	1.0e-08	0
Rotated High Conditioned Elliptic Function		1.0e-08	1.0e-08	1.0e-08	1.0e-08	0
Rotated Rosenbrock’s Function		7.8e-08	2.6e-05	3.8e-07	1.2e-06	7.3e-04
Rotated Schaffers F7 Function		1.0e-08	6.4e-02	3.0e-07	9.2e-04	6.7e-03
Composition Function 1		1.0e+02	4.0e+02	2.0e+02	1.7e+02	5.4e+01
Composition Function 2		2.8e+02	1.3e+03	7.4e+02	9.9e+02	2.4e+02
Sphere Function	50	1.0e-08	1.0e-08	1.0e-08	1.0e-08	0
Rotated High Conditioned Elliptic Function		1.0e-08	1.0e-08	1.0e-08	1.0e-08	0
Rotated Rosenbrock’s Function		3.6e-01	4.3e+01	4.3e+01	4.0e+01	8.2e+00
Rotated Schaffers F7 Function		1.0e-08	5.3e+00	8.7e-02	6.3e-01	1.3e+00
Composition Function 1		2.0e+02	1.3e+03	2.0e+02	4.8e+02	3.6e+02
Composition Function 2		6.7e+02	2.8e+03	1.2e+03	1.4e+03	5.9e+02

Table 6: Performance of LDABC on CEC-2013 problems for dimension 10, 30 and 50.

influence of population shape, neighborhood structure and step size to the performance of LDABC, and apply LDABC to solving some real-word optimization problems.

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