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Reduction of artificial bee colony algorithm for global optimization

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ABSTRACT

This paper presents a reduction of artificial bee colony algorithm for global optimization. Artificial bee colony algorithm is an optimization technique which refers to the behavior of honeybee swarms, and a multi-point search approach which finds a best solution using multiple bees. For avoiding local minima, a number of bees are initially prepared and their positions are updated by artificial bee colony algorithm. Bees sequentially reduce to reach a predetermined number of them grounded in the evaluation value and artificial bee colony algorithm continues until the termination condition is met. In order to show the effectiveness of the proposed algorithm, we examine the best value by using test functions compared to existing algorithms. Furthermore the influence of best value on the initial number of bees for our algorithm is discussed.

1. Introduction

By growing the large-scale and complexity of solving problems, it is difficult for optimization problem to obtain an optimal solution and the processing requires an immense amount of time. Metaheuristics have been a focus of attention for this situation since they can obtain an approximate solution as the polynomial time algorithm [1]. Metaheuristics are optimization approaches which make use of the best solution improved iteratively to the next search. Metaheuristics involve, for example, genetic algorithm (GA), differential evolution (DE), particle swarm optimization (PSO), and artificial bee colony (ABC) algorithm. GA is a search algorithm which carries out the genetic operation of selection, crossover, and mutation [2]. DE adopts mutation as a weighted sum of a base vector and a difference vector. An individual selected from the population becomes the basic vector and the difference between a pair of individuals becomes the difference vector [3]. PSO is a multi-point search algorithm using multiple candidate solutions called particles and performs the solution search by sharing huge amounts of information in each particle [4]. ABC algorithm is an optimization approach which refers to the behavior of honeybee swarms [5]. The motion model of honeybee consists of food sources, employed bees, onlooker bees, and scout bees. Although ABC algorithm can be applied to a number of optimization problems, the solution may fall into a local minimum and it is difficult to find an optimal solution for a complicated objective function such as a multimodal function with a lot of local minima. Various approaches have also been introduced for unit reduction, and many discussions have been made on the multilayer neural networks [6,7]. For the purpose of vector quantization, self-organizing algorithms are proposed for reduction techniques [8,9]. Meanwhile for optimization problems, there exists particle swarm optimization with reduction [10], but artificial bee colony algorithm with respect to reduction has not been proposed.

In this study, we present a reduction of artificial bee colony algorithm for global optimization. A number of bees are initially prepared and the positions of these are updated in artificial bee colony algorithm. Bees sequentially reduce to reach a predetermined number of them founded on the evaluation value and artificial bee colony algorithm continues until the termination condition is met. In order to show that our algorithm is effective in quality, experimental results are presented in comparison with existing algorithms. Moreover we examine the influence of best value on the initial number of bees for our algorithm.

2. Artificial bee colony algorithm

Artificial bee colony (ABC) algorithm is an optimization approach which refers to the behavior of honeybee swarms. The motion model of honeybee in the natural world consists of food sources and three kinds of bee swarms (employed bees, onlooker bees, and scout bees). ABC algorithm sends employed bees to food sources and intensively searches for around food sources with high fitness value by utilizing onlooker bees and scout bees. Bee swarms quests for food sources in the following description.

(1) *Phase of employed bees*: Each employed bee searches for food sources with high quality around food sources which relates

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to each employed bee. For all food sources $\boldsymbol{x}_i$ $(i=1,2,3,\dots,m)$, candidate positions of food sources $\boldsymbol{v}_i$ are calculated as follows:

$$\boldsymbol{v}_i=\boldsymbol{x}_i+\phi_i(\boldsymbol{x}_i-\boldsymbol{x}_j) \tag{1}$$

where ϕ_i is a uniform random number among $[-1,1]$ and $\boldsymbol{x}_j$ $(j\neq i)$ is determined randomly.

In comparison with positions $\boldsymbol{v}_i$ and $\boldsymbol{x}_i$, the position with best value becomes position $\boldsymbol{x}_i$.

(2) *Phase of onlooker bees*: In accordance with amounts of information obtained by the search of employed bees, onlooker bees search for neighborhoods of food sources with high evaluation intensively. Onlooker bees choose food sources based on probability p_i expressed as follows:

$$p_i=\frac{F_i}{\sum_{n=1}^{m}F_n} \tag{2}$$

where F_i is the fitness value of the search position $\boldsymbol{x}_i$ and m is the number of food sources.

Fitness value F_i is obtained by objective function $f(\boldsymbol{x}_i)$ represented as follows:

$$F_i=\begin{cases}\dfrac{1}{1+f(\boldsymbol{x}_i)}, & f(\boldsymbol{x}_i)\geq 0\\ 1+|f(\boldsymbol{x}_i)|, & f(\boldsymbol{x}_i)<0\end{cases} \tag{3}$$

(3) *Phase of scout bees*: For food sources $\boldsymbol{x}_i$ which are never updated at a predetermined number of iterations T_{limit} called limit number in the previous phases, the scout bee discovers a food source and replaces as follows:

$$\boldsymbol{x}_i=\boldsymbol{x}_{\min}+r(\boldsymbol{x}_{\max}-\boldsymbol{x}_{\min}) \tag{4}$$

where $\boldsymbol{x}_{\min}$ is the position of the minimum fitness, $\boldsymbol{x}_{\max}$ is the position of the maximum fitness, and r is a random number among $[0,1]$.

In ABC algorithm, the total number of bees which constitute a colony corresponds to the number of employed bees. The number of food sources equals to that of employed bees (total search points). ABC algorithm memorizes the best solution in an iteration after phases of three kinds of bee swarms and repeats until the termination condition is met.

3. Reduction of artificial bee colony algorithm

In this study, we present an artificial bee colony with reduction (ABCR) algorithm for avoiding local minima. A number of bees are prepared initially and bees are updated in ABC algorithm. Bees are sequentially reduced to reach a predetermined number of them based on the evaluation value and ABC continues until the termination condition is met. As a bee with the highest value of objective function is selected, the worst position of bee vanishes. ABCR algorithm is presented as follows.

ABCR Algorithm.

1. Initialization:
   1.1. Give initial number of bees m_0, final number of bees m_f, limit number T_{limit}, maximum iteration $T_{\max}$, and partial iteration $u=T_{\max}/(5(m_0-m_f+1))$.
   1.2. Yield initial position $\boldsymbol{x}_i^0$ for each bee at random.
   1.3. Set $k\leftarrow 0$, $m\leftarrow m_0$, and $\boldsymbol{g}^0\leftarrow\boldsymbol{x}_s^0$, where $s=\arg\min_i f(\boldsymbol{x}_i^0)$.
2. Processing of employed bees:
   2.1. New position $\boldsymbol{v}_i^k$ for employed bees are generated according to Eq. (1).
   2.2. In comparison with positions $\boldsymbol{v}_i^k$ and $\boldsymbol{x}_i^k$, the position with best value becomes position $\boldsymbol{x}_i^k$.
3. Processing of onlooker bees:
   3.1. Probability p_i^k is calculated according to Eq. (2).
   3.2. One search point $\boldsymbol{x}_c^k$ is selected by the roulette rule grounded in probability p_i^k. For only $\boldsymbol{x}_c^k$, candidate position $\boldsymbol{v}_c^k$ is produced, as in Step 2. In comparison with positions $\boldsymbol{v}_c^k$ and $\boldsymbol{x}_c^k$, the position with best value becomes position $\boldsymbol{x}_c^k$.
4. Processing of scout bees:
   For search points $\boldsymbol{x}_i^k$ which are never updated at T_{limit}, $\boldsymbol{x}_i^k$ is changed according to Eq. (4).
5. Reduction of bee:
   If $k=u\times q$ and $m>m_f$, then reduce bee j and set $m\leftarrow m-1$, where q is a positive integer and $j=\arg\max_i f(\boldsymbol{x}_i^{k+1})$
6. Update of best value:
   Set $\boldsymbol{g}^{k+1}\leftarrow\boldsymbol{x}_s^{k+1}$, where $s=\arg\min_i f(\boldsymbol{x}_i^{k+1})$.
7. Termination condition:
   If $k=T_{\max}$, then terminate, otherwise set $k\leftarrow k+1$ and go to Step 2.

4. Numerical experiments

In numerical experiments, we exhibit results of the proposed algorithm (ABCR) compared to real-coded genetic algorithm (RGA), differential evolution (DE), particle swarm optimization (PSO), and artificial bee colony (ABC) algorithm. We use six functions in two-dimensional space expressed in the following descriptions.

F_1 2^n minima function:

$$F_1(\boldsymbol{x})=\sum_{i=1}^{n}[x_i^4-16x_i^2+5x_i] \tag{5}$$

F_2 Rastrigin's function:

$$F_2(\boldsymbol{x})=10n+\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)] \tag{6}$$

F_3 Levy's function:

$$F_3(\boldsymbol{x})=\frac{\pi}{n}\left\{\sum_{i=1}^{n-1}[(x_i-1)^2(1+10\sin^2(\pi x_{i+1}))]\right.$$
$$\left.+10\sin^2(\pi x_1)+(x_n-1)^2\right\} \tag{7}$$

Table 1
Domain of test functions.

Function	Domain
F_1	$-5.0\leq x_i\leq 5.0$
F_2	$-5.0\leq x_i\leq 5.0$
F_3	$0.0\leq x_1\leq 4.0$, $0.0\leq x_2\leq 6.0$
F_4	$-500.0\leq x_i\leq 500.0$
F_5	$-2.0\leq x_i\leq 2.0$
F_6	$-60.0\leq x_i\leq 60.0$

Table 2
Position of minimal solution for each test functions.

Function	Position
F_1	$(-2.90,-2.90)$
F_2	$(0.0,0.0)$
F_3	$(1.0,1.0)$
F_4	$(420.9678,420.9678)$
F_5	$(-1.425,-0.800)$ or $(-0.800,-1.425)$
F_6	$(-32.0,-32.0)$