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Modification of Artificial Bee Colony Algorithm for Various Requirements

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1. Introduction

Optimization is to search optimal solution under condition. Benefit of optimization is high efficiency. Optimization is needed in various scenes. Combinatorial optimization problem is often solved by metaheuristic optimization algorithms.

Many combinatorial optimization problems often results in local optima. Metaheuristic optimization algorithms are provided good-quality solutions which are close to the optimal solution with less computational effort in these problems. These algorithms are developed to solve more efficiency and larger problems. Metaheuristic optimization algorithms have Evolutionary Algorithm (EA), Swarm Intelligence (SI) algorithm, local search, etc. In our study, we choose the SI.

SI is one of the artificial intelligence techniques. SI was born from swarm of insect. Examples existing in nature are ant, bee and firefly, etc. In insect colonies, each insect has its the group in total appears to be highly organized. The applications of SI technique are a self-driving car and data mining. The good points of this technique are smaller control system and multi control by simple systems. SI algorithms have Artificial Bee Colony Algorithm (ABC), Ant Colony Optimization(ACO), Particle Swarm Optimization (PSO), Firefly Algorithm (FA), etc [1]. ABC is used by our propose method.

ABC is idealized the social behavior of bees based on their feeding characteristics. ABC was proposed by Karaboga Dervis in 2005 [2]. Artificial intelligence algorithms have been demonstrated to show effectiveness and efficiency to solve difficult optimization problems [3]. ABC performs higher ability in high dimensional optimization problem than other SI algorithms. However, demerit of ABC is that it can not search time-varying function.

In previous study, we modified ABC for time-varying function (ABCTV) [4]. However, we can not find accurate solution. [5]

In this study, we propose ABCTV in which the employed bee is improved by predictive value. We compare the best value of the solution with ABC, ABCTV and the proposed method.

2. Experimental setup

The most of algorithms exclude time-varying solution. However, when we search optimal solution, we need to apply the both solutions (time-varying and not time-varying). In case of ABC, it can not be performed adapted to environmental changing such as shifts in the optimal solution or variations of the cost function. The artificial bee colony algorithm for time-varying solution (ABCTV) is proposed. ABCTV was modified 2 points. First, when employed bee compares fitness function values between 2 locations, previous location is re-evaluated for each simulation count. Second, we calculate best fitness function value for each simulation count. According to these modification, ABCTV can search time-varying solution. However, ABCTV can not search accurate solution than the standard ABC.

We propose ABCTV in which the employed bee improves by prediction. The employed bee searches a new location by Eq. (1) in the standard ABC. However, ABC has problem point that the best solution follow for optima. Therefore, we modify that the employed bee searches new location by the prediction position. The prediction position is calculated difference of the employed bee between current best location and the previous best location. According to we assume the optimal solution is uniform motion, we predict the location of the next optimal solution from the difference between the two locations. Furthermore, we use equation of PSO to append the predictive value. In PSO, position is calculated by Eq. (2).

$$v_{id}(t+1) = x_{id}(t) + \varphi_{id}\left(x_{id}(t) - x_{kd}(t)\right) \quad (1)$$

$$v_{id}(t+1) = x_{id}(t) + \varphi\left(x_{ij}(t) - x_{kj}(t)\right) + \psi\left(y_j(t) - x_{ij}(t)\right) \quad (2)$$

where y_j is information of global best solution and x_{kj} is information of local best solution. PSO use information of global best solution to guide searching. This convert the predictive value. From the beginning of the simulation employed bee searches new location by using Eq. (3).

$$v_{id}(t+1) = x_{id}(t) + \varphi_{1id}\left(x_{id}(t) - x_{kd}(t)\right) + \varphi_{2id}\left(x_{predict}(t) - x_{kd}(t)\right) \quad (3)$$

φ is a uniform random parameter in [0, C], where C is a nonnegative constant. In this study, we set 5 kinds C (0.5, 1.0, 2.0, 3.0, 4.0). Furthermore, the proposed method is expected to have better performance by combining improved ABCTV and ABC.

3. Results and discussion

Firstly, in order to evaluate the performance of the propose method, we compare the result of Eq. (4). Figure 1 shows the shape of this function.

$$g(x_1, x_2, t) = 1 - exp\left[-\frac{(x_1 - 250 - 125sin\alpha t)}{2 \cdot 40^2} - \frac{(x_2 - 250 + 125cos\alpha t)}{2 \cdot 40^2}\right] \quad (4)$$

Equation (4) simulates a visual tracking problem. The distribution of the minimum value represented by a Gaussian function moves continuously in the figure, and the problem of tracking this movement is assumed. The optimal function value is 0, and position along a circle of radius 125 centered at $(x_1,\ x_2)$ = (250, 250), then return its original position in $(2\pi/\alpha)$ steps. k means time that is approximated by simulation count. We express the constant value to use for simulation in Eq. (5).

$$v_{id}(t+1) = x_{id}(t) + \varphi n_e = n_o = 50, t_{max} = 100000 \quad (5)$$

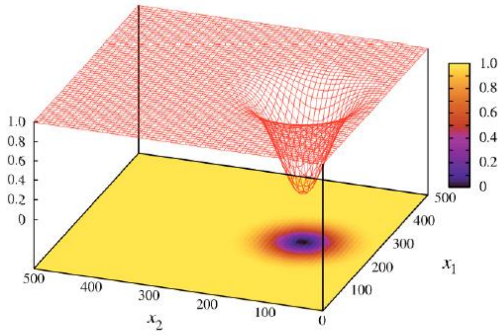

Fig. 1. Shape of unimodal time-varying function

We compare the best value for 7 kinds movement speed of optimal solution α (α = 0.01, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30). The best solution is the smallest value in results of 15 times simulations. Table 1 shows that the best value of each method. From Table I, the best value of the propose method is better than the best value of ABCTV. Especially, the propose method when C = 3.0 has best performance. However, many of the proposed methods become less effective as α increases. This is reason that the movement of the solution becomes discrete as α increases.

Table 1. Simulation result (unimodal time-varying)

Method	:0.01	:0.05	:0.10	:0.15	:0.20	:0.25	:0.30
ABC	1.08e-08	1.11e-06	4.11e-06	4.51e-06	3.12e-06	4.55e-06	6.08e-06
ABCTV	4.12e-07	3.34e-06	9.96e-05	7.33e-05	2.96e-04	1.43e-04	2.77e-05
C=0.5	2.26e-08	6.47e-06	6.75e-06	3.33e-05	2.62e-06	6.53e-06	1.56e-05
C=1.0	9.21e-08	3.84e-07	3.90e-07	6.39e-06	5.94e-06	1.07e-05	5.96e-05
C=2.0	1.55e-08	4.35e-07	8.59e-06	7.12e-06	2.92e-05	1.33e-05	6.71e-06
C=3.0	4.28e-09	4.28e-09	3.52e-06	1.05e-05	9.34e-07	4.01e-07	7.16e-06
C=4.0	4.31e-08	1.18e-06	1.99e-06	1.06e-05	3.16e-05	3.88e-06	1.56e-05

Secondly, we confirm the proposed method has the ability to search for multimodal time-varying solutions. We compare the result of Eq. (6).

$$g(x_1, x_2, t) = 1 - \left[\frac{\sin \beta t + 1}{2} exp\left\{-\frac{1}{2}\left(\frac{(x_1 - 125)^2}{40^2} + \frac{(x_2 - 375)^2}{40^2}\right)\right\} + \frac{\sin(-\beta t) + 1}{2} exp\left\{-\frac{1}{2}\left(\frac{(x_1 - 375)^2}{40^2} + \frac{(x_2 - 125)^2}{40^2}\right)\right\}\right] \quad (6)$$

Figure 4 shows the shape of this function. Multiple depressed area expressed by Gaussian function move discontinuously by repeating appearance and disappearance. Optimal value is assumed to be between 0 and 0.5. The optimal position is switched between (125,375) and (375, 125) in a set period. β means variation of object function for each step. From Table 2, the best value of the propose method is better than the best value of ABCTV and ABC. Especially, the propose method when C = 0.5 has best performance.

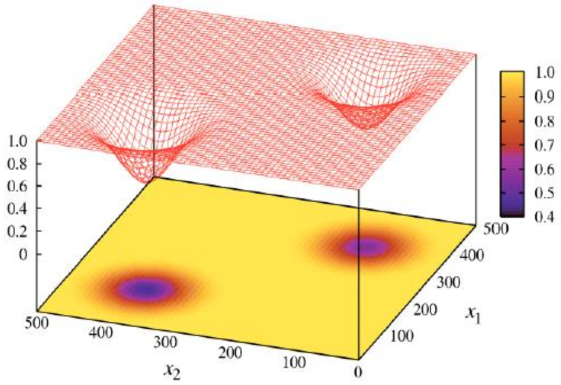

Fig. 2. Shape of multimodal time-varying function

Table 2. Simulation result (multimodal time-varying)

Method	β:0.01	β:0.05	β:0.10	β:0.15	β:0.20	β:0.25	β:0.30
ABC	2.63e-07	2.79e-06	2.71e-06	4.48e-06	1.37e-06	7.21e-06	4.37e-07
ABCTV	6.24e-04	3.33e-04	1.48e-04	9.59e-05	9.90e-05	1.13e-04	2.42e-05
C＝0.5	4.02e-08	2.98e-07	9.68e-09	2.76e-07	2.47e-08	2.16e-08	4.69e-08
C＝1.0	4.88e-06	2.98e-05	1.86e-05	7.77e-05	4.96e-05	1.25e-04	1.28e-04
C＝2.0	1.21e-05	8.32e-06	3.21e-05	1.86e-05	3.44e-05	2.15e-06	7.47e-06
C＝3.0	1.10e-05	1.17e-04	4.98e-06	1.01e-04	7.25e-05	3.63e-05	2.96e-04
C＝4.0	2.21e-05	2.91e-04	2.34e-04	1.20e-05	2.62e-04	1.52e-04	4.73e-04

4. Conclusion

This study shows ABC modified that employed bee is changed by predictive value because this algorithm do not applied for accurate time-varying solution. We tried improvement of ABC, where employed bee searches new position by predictive value. The predictive value is calculated by difference between best solutions by assuming that optimal solution is constant motion. Furthermore, the predictive value is append searching equation of employed bee by inspired from PSO. We set the proposed method has 5 kinds of range of random value. We compared the best values of the proposed method, the previous method and ABC. As a result, even if optimal solution is discrete, the proposed method could search better value than other algorithms. Therefore, the proposed method is better performance than other methods. In the future work, we would like to investigate the mechanism of the proposed method in detail. Furthermore, we try to search high dimensional problems.

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