Pheromone-Based Bees Algorithm

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1. Introduction
Bees Algorithm (BA) is a popular optimization method for the solution of object function and is an evolutionary algorithm to simulate the food foraging behavior of honey bees. In BA, the algorithm performs a kind of neighbourhood search combined with random search and can be used for both combinatorial optimization problems and functional optimization problems.

In this study, we propose Pheromone-Based BA (PBBA). The important feature of PBBA is that all bees are influenced by the pheromone. We apply PBBA to functional optimization problems and confirm its effectiveness.

2. Pheromone-Based Bees Algorithm

[PBBA1] Initialization: Let the generation step \( t = 0 \) and the converge step \( t_R = 0 \). Randomly initialize the search bees \( i = (1, 2, ..., M) \) position \( X_i = (x_i1, x_i2, ..., x_iD) \). \( D \) is dimension parameters.

[PBBA2] Dispose the recruit bees \( j = (1, 2, ..., N) \) around each \( X_i \). The recruit bees position \( r_{ij} \) is decided by
\[
\begin{align*}
    r_{ij} &= x_i(t) + \Delta \phi_{ij}(t), \\
    \Delta \phi_{ij} &= (S_i(t) Q_{ij}, \theta_{ij}),
\end{align*}
\]
where \( \Delta \phi_{ij} \) is the polar coordinate. \( Q_{ij} \) is the random variables distributed uniformly on \([0,1]\). \( \theta_{ij} \) is the amplitude and is the random variables distributed uniformly on \([0, 2\pi]\). \( S_i \) is the largest search range.

[PBBA3] Evaluate the all current recruit bees cost \( f(R_{ij}) \). Update the search bees position \( X_i \) for each \( i \).

[PBBA4] If \( X_i(t + 1) \leq X_i(t) \): perform [PBBA5].
If \( X_i(t + 1) > X_i(t) \): Update each \( X_i \), let \( t_Ri = 0 \) and perform [PBBA6].

[PBBA5] If \( t_Ri < T_Ri \): Let \( t_Ri = 0 \) and initialize \( S_i \).
If \( t_Ri > T_Ri \): \( S_i(t + 1) = 0.9 S_i(t) \).

[PBBA6] Evaluate the current cost \( X_i \). Update the global best position \( x_{gbest} \) among all \( X_i \). \( X_i(t + 1) \) is updated according to \( X_{gbest} \). The important feature of PBBA is that the all bees \( X \) are influenced by a pheromone. A pheromone is disposed in the whole group’s best position \( X_{gbest} \). The \( X_i \) is updated depending on the best position \( X_{gbest} \).
\[
X_i(t + 1) = X_i(t) + c Q(x_{gbest} - x_i),
\]
where the parameter \( c \) is positive acceleration coefficients.

[PBBA7] Let \( t = t + 1 \) and \( t_Ri = t_Ri + 1 \). Go back to [PBBA2], and repeat until \( t = T \).

3. Numerical Experiments
In order to evaluate the performance of PBBA, we apply PBBA to two functional optimization problems and compare PBBA with existing two algorithms. One is the standard BA and the other is the standard Particle Swarm Optimization (PSO). PSO is based on pheromone action as similar to PBBA.

We carry out the simulation 10 times for two optimization functions; Sphere function and Rastrigin function, with 2000 generations. A dimension is 100. The optimum function values of the two functions are 0. Fig. 1(a) shows the mean value of \( gbest \) for Sphere function and Fig. 1(b) shows the mean value of \( gbest \) for Rastrigin function. From these results, we can see that the mean values of PBBA are the best for the two problems.

Figure 1: Mean \( gbest \) value of every generation. (a) Sphere function. (b) Rastrigin function.

4. Conclusions
In this study, we have proposed Pheromone-Based Bees Algorithm (PBBA) and have solved two functional optimization problems. We have confirmed that PBBA obtained better results than the standard BA and the standard PSO.

References