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Special Focus on Pigeon-Inspired Optimization

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Comprehensive learning pigeon-inspired optimization with tabu list

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Dear editor,
During the last decade, population-based algorithms have been extensively used to solve multimodal, discontinuous, non-convex, and nondifferentiable optimization problems. These algorithms search for the best solution by applying some operators and strategies over a set (population) of potential solutions (individuals). All those operators or strategies follow one principle: balancing between exploration and exploitation, which are the two cornerstones of problem-solving by searching [1]. Therefor, a good population-based algorithm needs to establish an appropriate ratio between exploration and exploitation [2].

Pigeon-inspired optimization (PIO) algorithm is a new class of bio-inspired swarm intelligence algorithm. It simulates the process of homing pigeons by finding paths that contain two operators: map and compass operator and landmark operator. The former instructs pigeons to adjust its flying direction by following a specific pigeon, and the latter helps pigeons fly straight to the destination by following the center of positions of some pigeons. Studies demonstrate that PIO can provide wider search space and faster convergence speed compared with other advanced algorithms. PIO can easily obtain a globally optimal solution [3]. However, the basic PIO algorithm has some limitations, which may restrict its solution to a local optimum or suffer from premature convergence, particularly in solving large-scale complex optimization problems.

This study presents a comprehensive learning PIO with the tabu list (CLPSO-TL), which uses comprehensive learning (CL) strategy and an adaptive adjustment mechanism to promote pigeons' learning ability with varying degrees. PIO also uses the tabu list (TL) to avoid unnecessary search in the dissatisfactory area. In CLPIO-TL, each pigeon follows its exemplar that comprises the population's best experience in different dimensions. Based on the prohibition and aspiration criterion, a better neighbourhood solution will be constructed in each iteration. Adaptive mechanisms are also used in CLPIO to enhance the balance between exploration and exploitation.

Algorithm framework. To enhance the exploration ability of pigeons, CL strategy [4] is chosen to generate exemplars as a learning object of the population. Instead of following the experience of only the best pigeon, the whole population learns from specific exemplars that consist of all pigeons' best experiences in different dimensions. Furthermore, the mechanism of tabu list is used to avoid invalid repeated search around the recent positions of the pigeons.

In the map and compass operator of CLPIO, the exemplar of pigeon is composed of different personal best experiences in different dimensions. Pigeon's velocity is updated according to inertia

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velocity and vectors between exemplar and current position using the following equation:

$$V_i^d(t+1) = V_i^d(t) \cdot \mathrm{e}^{-Rt} + c \cdot \mathrm{rand}_i^d \cdot (\mathrm{pbest}_{f_i(d)}^d - X_i^d(t)), \tag{1}$$

where $f_i(d) = [f_i(1), f_i(2), \ldots, f_i(D)]$ indicates that the ith pigeon follows its own or others' pbest^d in the dth dimension, and that the decision depends on probability Pc. Different pigeons have different learning ability, i.e., Pc_i is the probability that pigeon i would follow others instead of its own. The value of Pc_i is described as follows:

$$\mathrm{Pc}_i = \alpha + \beta \cdot \frac{\exp((10(i-1))/(N-1)) - 1}{\exp(10) - 1}, \tag{2}$$

where α and β determine the learning probability bound, namely $\mathrm{Pc}_i \in (\alpha, \alpha+\beta]$. Thus, the pigeons' learning probabilities are gradually increasing along with the serial number. A random number is generated that is compared with Pc_i. If the random number is large, pigeon i chooses its own pbest^d as the learning exemplar. Otherwise, the ith pigeon's flying direction is guided by one of other pigeons' pbest^d, which is determined via tournament selection. Therefore, the exemplar $\mathrm{pbest}_{f_i(d)}$ is a position that contains hybrid information from several pigeons' pbest in different dimensions. Moreover, the exemplar will be updated when the ith pigeon's fitness is not promoted in several successive iterations.

The landmark operator also allows pigeons to learn from exemplar generated via the CL strategy with the learning probability Pc_i. Thus, the pigeons fly straight to the landmark determined by the central position X_{center} and exemplar $\mathrm{pbest}_{f_i(d)}^d$ using (3). Moreover, the acceleration coefficients c_1 and c_2 are introduced on X_{center} and $\mathrm{pbest}_{f_i(d)}^d$ to accelerate the speed of convergence speed. Further, c_1 increases gradually as c_2 decreases such that the influence of center position become more important in later period.

$$X_i(t+1) = X_i(t) + c_1 \cdot \mathrm{rand} \cdot (X_{\mathrm{center}}(t) - X_i(t)) + c_2 \cdot \mathrm{rand} \cdot (\mathrm{pbest}_{f_i(d)} - X_i(t)). \tag{3}$$

Although CL strategy and tabu list are introduced to enhance exploration ability, the algorithm is likely to get trapped into local optimum. To guarantee algorithm efficiency, the search direction should be adjusted as the requirement. When less improvement is obtained in several iterations, the possibility of population falling into the local optimum increases. The adaptive adjustment mechanism denotes a variable refresh gap rg to record the number of times pigeons' positions are not improved constantly. The rg of pigeon i is updated based on the following equation:

$$\mathrm{rg}(i) = \begin{cases} \mathrm{rg}(i)+1, & F(X_i(t+1)) < F(X_i(t)), \\ 0, & F(X_i(t+1)) > F(\mathrm{pbest}_i). \end{cases} \tag{4}$$

As rg increases, the possibility of falling into local optimum is increased; this means that a pigeon should adjust its search direction. In this algorithm, the exemplar will be updated according to the CL strategy under the condition $\mathrm{rg} < \tau$ and $\tau = 5$ will be employed according to a previous study [3].

To encourage pigeons flying to the new region, the tabu list is formed to record optimization procedure and guide the next search direction. Furthermore, an aspiration criterion of the tabu list is adopted to avoid missing the movement of the best solution. After a pigeon obtains a new position, δ_1 denotes the gap of fitness between the new and current positions and the gap of fitness between the new and personal best positions pbest is δ_2. Thus, we have

$$\delta_1(i) = F(X_i(t+1)) - F(X_i(t)), \tag{5}$$

$$\delta_2(i) = F(X_i(t+1)) - F(\mathrm{pbest}_i). \tag{6}$$

Evidently, $\delta_1(i) > 0$ as the pigeon i moves to a better position than the last iteration; $\delta_2(i) > 0$ as the pigeon i moves to the best position than all other iterations. The procedure of prohibition and aspiration criterion is described below in detail:

- When $\delta_1(i) < 0$, let the new position be the exact position of the next iteration, i.e., $X_i(t+1) = X_i(t+1)$. Append $X_i(t+1)$ at the end of the tabu list.
- When $\delta_2(i) > 0$, let the new position be the exact position of the next iteration and refresh pbest, i.e., $X_i(t+1) = X_i(t+1)$ and $\mathrm{pbest}_i = X_i(t+1)$. Append $X_i(t+1)$ at the end of the tabu list.
- When $\delta_1(i) > 0$ and $\delta_2(i) < 0$, check whether the new position exists in the tabu list. If it does not exist, let $X_i(t+1) = X_i(t+1)$ and append $X_i(t+1)$ at the end of the tabu list. Otherwise, let $X_i(t+1) = X_i(t)$.

The Euclidean distance is used to measure the distances between the positions of the tabu list and the new position. The new position is considered to exist in the tabu list when any of the distances is less than the predetermined value radius. To enhance the exploration in the preceding period, radius is assigned a large initial value and it decreases gradually. The tabu list's limited "memory" ability also allows pigeons to fly back to a new position. Hence, the earliest position is released from the tabu list when the number of positions in the tabu list is out of the list's length. However, the tabu list with a too long or too short length may result in the loss of global optimum or repetitive searching. The tabu list strategy is not used on the landmark operator, thereby protecting the exploitability of landmark operator.

$$\text{radius} = V_{\max} \cdot \frac{1-T}{T}, \tag{7}$$

$$\text{length} = N \cdot \sqrt{(D)}. \tag{8}$$

Moreover, if the new position $X_i(t+1)$ exists in the tabu list, the adaptive adjustment mechanism will perform $\text{rg}(i) = \text{rg}(i)+1$ to help pigeon adjust the search direction.

Experimental study. Herein, the 25 CEC'2005 benchmark functions are used to verify the performance of the proposed CLPIO-TL algorithm. Five variants of PIO (i.e., basic PIO, predator-prey PIO, bloch quantum-behaved PIO, simulated annealing PIO, and Gaussian PIO) [5–8] are compared with the CLPIO-TL. Result indicates that the proposed CLPIO-TL can converge with an ideal convergence speed. Among most multimodal functions, the diversity of CLPIO-TL algorithm caused it to jump out of the local optimal at the early phase and achieve a better performance rapidly. As shown in Figure 1, the CLPIO-TL maintains a good speed of convergence within a complex search space on rotated hybrid composition function. In this case, CLPIO-TL does not produce the best result initially; the population immediately adjusts its search direction and accelerates the searching speed according to the iterations.

Conclusion and future work. By employing of a CL strategy, the population can follow different personal best experience in different dimensions and reinforce the diversity of the population. The prohibition and aspiration criteria of the tabu list are adopted to help pigeons avoid revisit solutions that are recently considered in the short term and bias the search toward promising areas of the search space in the intermediate-term. This enables the driving of population to new regions and improving the exploration ability. Our future work focuses on improving CLPIO-TL and investigating its applications to address practical problems.

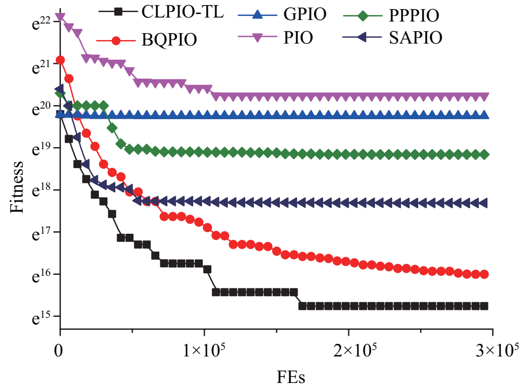

Figure 1 (Color online) Comparison between the experimental results of CLPIO-TL and PIO variants.

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References

1 Eiben A E, Schippers C A. On evolutionary exploration and exploitation. Fundam Inf, 1998, 35: 35–50
2 Črepinšek M, Liu S H, Mernik M. Exploration and exploitation in evolutionary algorithms. ACM Comput Surv, 2013, 45: 1–33
3 Duan H, Qiao P. Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning. Int J Intell Comput Cyber, 2014, 7: 24–37
4 Liang J J, Qin A K, Suganthan P N, et al. Comprehensive learning particle swarm optimizer for global optimization of multimodal functions. IEEE Trans Evol Comput, 2006, 10: 281–295
5 Li H, Duan H. Bloch quantum-behaved Pigeon-inspired optimization for continuous optimization problems. In: Proceedings of Guidance, Navigation and Control Conference. New York: IEEE, 2014. 2634–2638
6 Zhang B, Duan H. Predator-prey pigeon-inspired optimization for UAV three-dimensional path planning. In: Proceedings of International Conference in Swarm Intelligence. Berlin: Springer, 2014. 96–105
7 Zhang S, Duan H. Gaussian pigeon-inspired optimization approach to orbital spacecraft formation reconfiguration. Chin J Aeronaut, 2015, 28: 200–205
8 Li C, Duan H. Target detection approach for UAVs via improved pigeon-inspired optimization and edge potential function. Aerospace Sci Tech, 2014, 39: 352–360