

Research and Implementation of Hybrid Bat Algorithm

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Keywords: Simulation trajectory, precocious processing variation mechanism, dynamic step.

Abstract: UAV path planning is a multi-constrained optimization problem that finds the optimal path under the constraints of distance, obstacle avoidance and equilibrium constraints. This paper proposes a hybrid bat algorithm (HBA) which improves the traditional bat algorithm by adding precocity processing, mutation mechanism and dynamic step size, and simulates UAV path planning by simulating mountains. Compared with the classic BA algorithm, it can be seen that the hybrid bat algorithm effectively solves the problem of easy prematureness of the algorithm, improves the accuracy of the algorithm, and provides a solution for UAV path planning.

1. Introduction

Aircraft path planning, its essence is a system optimization problem with complex constraints. There are a series of methods for track planning, the core of which is the track planning algorithm. Many foreign scholars have done a lot of research on drone track planning algorithms, such as: multiple optimization algorithms, RRT algorithms, biological heuristic algorithms, etc.

Nature is the source of all things and it is enlightening. For example, a bat can display super intelligence, which is embodied in that it can perfectly avoid obstacles and smoothly forage while flying. Bat Algorithm (Bat Algorithm, abbreviation BA) is an intelligent optimization meta heuristic algorithm smart proposed by Cambridge scholar Xin-She Yang[1] in 2010. Ping Zhao[2] combined with the current research of bat algorithm, proposed the problems that the bat algorithm needs to be improved and paid attention to in the future, and looked forward to the future research direction; A hybrid genetic bat algorithm (HGBA) was proposed for the flexible job shop scheduling problem with the goal of minimizing the maximum completion time; Xiaomeng Li[5] simulated a clustering behavior of marine organisms and sea squirts during navigation and feeding in the ocean Intelligent algorithm of Zunhai sheath group; Yanyan Du [7] proposed a modified adaptive hybrid bat algorithm, using the shrinkage factor to balance the local and global search in the bat algorithm; Shilei Lu[8] proposed an improved bat algorithm (SABA), adding adaptive step control mechanism and mutation mechanism. Baolei Li[4] used a multivariate optimization

algorithm to search for elements through overall and local alternating optimization; Haohao Cheng[9] proposed a comprehensive improved RRT algorithm. Chenyue Mao[6] proposed an unmanned aerial vehicle path planning obstacle avoidance algorithm based on the artificial potential field method.

Aiming at the shortcomings of the basic bat algorithm, such as the low precision of optimization and the premature convergence, this paper adding premature mechanism, mutation mechanism and step to the traditional BA algorithm improvement of long limit, which proposed hybrid bat algorithm HBA.

2. UAV Track Planning Model

UAV path planning refers to designating the starting point and end point of the drone flight under known or unknown environmental conditions, the drone autonomously completes the design of the flight path, and guarantees that certain flight indicators are optimal. In this paper, the trajectory planning of the UAV is simulated by simulating the mountains.

2.1. Map Building

Drone path planning is an important part of the autonomous flight of drones. Two principles need to be followed in the construction of mountain mathematical models:

1. The positions of the peaks are random, simulating the natural environment.
2. The size of the peaks is random.

The simulation is performed by a computer. The simulation map of a certain time is shown in the following figure, where the Figure 1 is a two-dimensional representation.

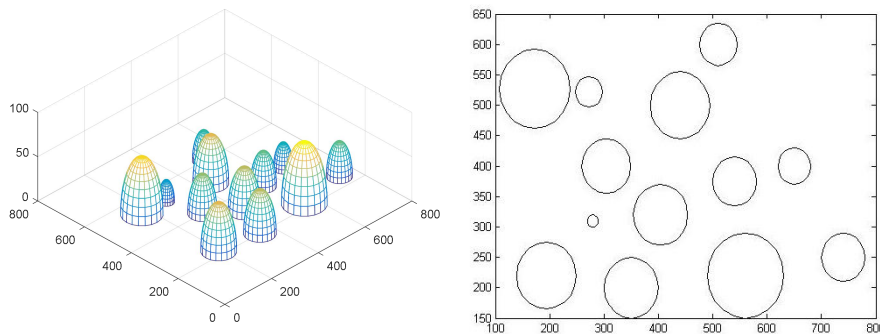


Figure 1: Mountain simulation map.

2.2. Planning Model

Remember X_i as the coordinate set of all points passed by the drone, where path is the path set and cost is the cost function matrix, then :

$$X_i = (\underbrace{x_{i1}, x_{i2}}_{\text{drone passing coordinates } P_{i1}}, x_{i3}, x_{i4}, \dots, \underbrace{x_{iD-1}, x_{iD}}_{\text{Drone passing coordinates } P_{iD}}) \quad (1)$$

$$path = (p_{i1}, p_{i2}, p_{i3}, \dots, p_{iD}) \quad (2)$$

$$\text{cost}_{(ii,ii)} = \sqrt{(x_{ii} - x_{ii-1})^2 + (y_{ii} - y_{ii-1})^2} \quad (3)$$

For obstacle avoidance, we can get $d = \frac{|Ax_0 + By_0 + C|}{\sqrt{A^2 + B^2}} - R$, among them $A = y_{i+1} - y_i$, $B = x_i - x_{i+1}$, if the path point of the drone does not intersect or tangent to the mountain peak, the path is a feasible path, that is, d is a real number greater than 0 at this time.

3. Improved Bat Algorithm

3.1. Traditional Bat Algorithm

The idealized rule of the bat algorithm is as follows: all bats perceive the distance through echolocation; it is known that the bat can automatically adjust the frequency and pulse emission rate of the transmitted pulse $r \in [0,1]$, when flying at x_i random at speed v_i with fixed frequency f_{min} , changing wavelength λ and loudness A_0 searching for prey; Suppose the range of loudness changes is $A_0 \sim A_{min}$ Frequency range is $[f_{min}, f_{max}]$, The corresponding wavelength range is $[\lambda_{min}, \lambda_{max}]$.

Objective function $f(x)$, $x = (x_1, \dots, x_d)^T$, Initialize bat population $x_i (i=1, 2, \dots, n)$ and v_i , Definition f_i as pulse frequency at x_i , initialization pulse rate r_i and loudness A_i . In each iteration, a new solution is generated by adjusting the frequency and the speed and position are updated. For updating the bat's position in the D-dimensional search space x_i and search speed v_i using time step as new solution x_i^t and speed v_i^t :

$$f_i = f_{min} + (f_{max} - f_{min})\beta \quad (4)$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_{best})f_i \quad (5)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (6)$$

Among them, $\beta \in (0,1)$ is a random quantity extracted from a uniform distribution. It's here, x_{best} is the current global best position, it is positioned after comparing all solutions in all bats. $\lambda_i f_i$ is the speed increment, using f_i / λ_i to adjust speed changes, while fixing another factor λ_i / f_i . Initially, each bat was randomly assigned a frequency, f_i is the transmission frequency, the value range is $[f_{min}, f_{max}]$.

For the local search part, once a solution is selected in the current best solution, use random walk to continue searching in the current optimal solution attachment

$$x_{new} = x_{best} + \lambda A^t \quad (7)$$

Among them, $\lambda \in [-1,1]$ is a constant, however, A^t is the average loudness of all bats at this time step.

In addition, as the iteration progresses, the loudness must be updated accordingly A_i and pulse emission rate r_i . Increased pulse emission with arbitrary loudness values. Suppose $A_{\min} = 0$ means that the bat has just found its prey and temporarily stopped making any sounds, then:

$$A_i^{t+1} = aA_i^t \quad (8)$$

$$r_i^{t+1} = r_i^0 [1 - \exp(-\gamma t)] \quad (9)$$

In fact, Cooling factor α similar to cooling schedule in simulated annealing. For any $0 < \alpha < 1$ and $\gamma > 0$, We have:

$$\text{when } t \rightarrow \infty, A_i^t \rightarrow 0, r_i^t \rightarrow r_i^0$$

3.2.Improved Bat Algorithm

Although the bat algorithm has a strong biological background, it is still in the development stage. Although it is widely used in practical problems, there are problems such as premature convergence of the group and weak local search ability in algorithm optimization. The reason why the algorithm is precocious is that before the optimal solution is obtained, the group has lost its diversity and converged to the local optimal solution in advance. The traditional bat algorithm cannot always achieve convergence at the global optimum, but it must add a certain Constraints can achieve global optimum. In view of the existing shortcomings of the BA algorithm, this paper proposes an improved bat algorithm. By adding Gaussian perturbation to the premature mechanism, it is confirmed that after the precocity, the bat population performs a mutation operation, so that the bat population that is trapped in the local optimum "shocks". In order to get rid of the local optimum, and then improve the search step size of the bat individuals, the bat population converges quickly in the early stage and slowly converges in the late stage, and the accuracy of solving the mathematical model is more accurate.

3.2.1. Inhibit Precocity

Before the bat algorithm started, refer to the differential evolution algorithm's treatment of the precocious mechanism in order to increase the diversity of the bat population, We define the precocity factor χ , then:

$$\chi = \frac{1}{N} \sum_{i=1}^N p_i \quad (10)$$

Among them, N set as population number, p_i set as the value for each individual. Define the normalization coefficient. Then $\zeta = \frac{1}{N} \sum_{i=1}^N (\frac{p_i - \chi}{p})$, Where p is $p = \max\{1, \text{abs}(p_i - \chi)\}, i \in [1, N]$. Premature threshold $T = \text{std}(f(x))$, where std is the function used to calculate the standard deviation, and $f(x)$ is the fitness function.

3.2.2. Mutation Mechanism

From the formula, when the number of iterations is enough, the loudness A will gradually drop to 0, The transmission frequency r increases to 1. At this time, the individual cannot perform the

mutation operation, and the algorithm easily falls into a local optimum. Therefore, the mutation operation is improved, and whether it is precocious is judged before the mutation operation, if $\zeta < T$ then enter the mutation operation. The mutation rules are as follows

$$A_i^{t+1} = \frac{f_1}{f_{\max}} \quad (11)$$

$$r_i^{t+1} = \frac{f_2}{f_{\max}} \quad (12)$$

Among them f_{\max} is the maximum value of bat pulse frequency. By limiting the range of emission frequency r and loudness A , the algorithm can effectively mutate the population in the later iterations.

3.2.3. Dynamic Step Size

A linear weighting method is introduced to dynamically update the step size, where the targeted formula 5 can be improved to

$$v_i^{t+1} = \sigma v_i^t + f_1 rand_1(x_{best} - x_i^t) + f_2 rand_2(x_{best} - x_i^t) \quad (13)$$

Among them σ set as weighting factor, used to dynamically adjust the global and local optimization characteristics of bats: when the algorithm searches early. At this time σ state at high level .The algorithm focuses on global search. As the number of iterations increases, the later stage is small. At this time, the local search capability of the algorithm is enhanced.

In summary, the flow of the hybrid bat algorithm is summarized as follows, and the specific algorithm flowchart is shown in Figure 2.

Table 1: Algorithm hybrid bat algorithm flow.

Step1: Initialization of Bat Population Parameters and Solving Precocious Coefficient ζ .
Step 2: Stochastic map simulation with Monte Carlo.
Step 3: Build a model to solve the fitness function $f(x)$.
Step 4: Update speed v , position x , and loudness A and emission frequency r .
Step 5: Determine if it is premature, and if it is premature, perform an improved mutation operation.
Step 6: Update the step size again and solve the model fitness value again.
Step 7: Update bat individual and population locations.
Step 8: Determine whether the final conditions are met, if it is met, end, otherwise go to step 3.

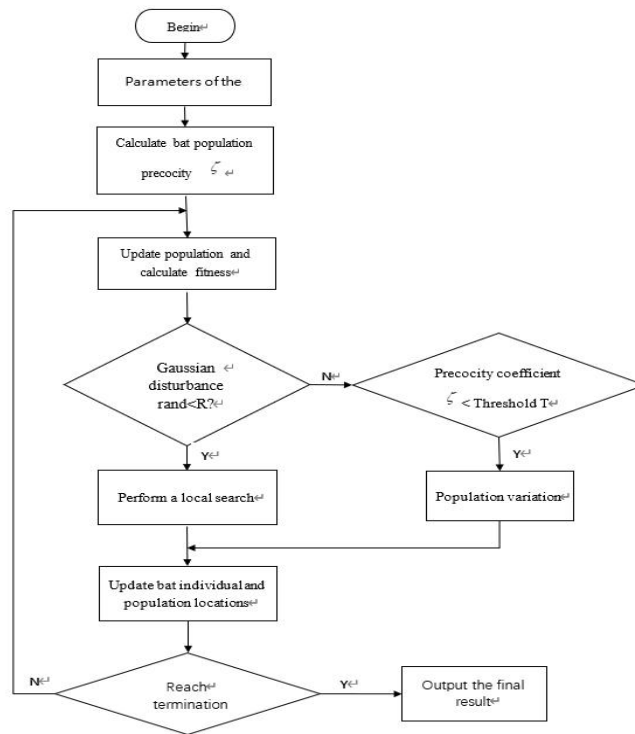


Figure 2: Algorithm flowchart.

4. Simulation Results and Analysis

To prove the effectiveness and reliability of the algorithm in this paper, the traditional BA algorithm is selected for comparison experiments, and simulation experiments are performed on the matlab software platform. The parameters in the experiment are set as follows:

Hybrid Bat Algorithm, maximum pulse frequency $f_{\max} = 0.65$, minimum pulse frequency $f_{\min} = 0$. Population number $N = 20$, go through 500 iterations. Maximum transmitting pulse frequency $r_{\max} = 1$, Inertia weight $\lambda = 0.8$.

Traditional BA algorithm: the basic parameters are consistent with HBA, where the emission range of the pulse frequency is $[-1.8 \ 0]$ and the range of loudness A is $[0, 2]$.

As shown in the Figure 3, it is a three-dimensional display of the simulation results of the HBA algorithm, and the Figure 4 is a two-dimensional cross-sectional view.

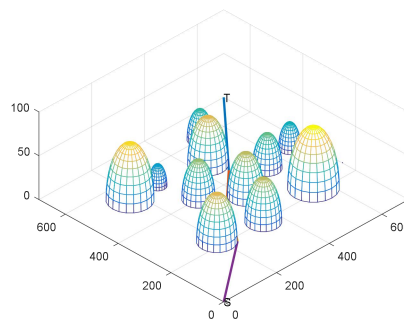


Figure 3: Comparison of optimization curves.

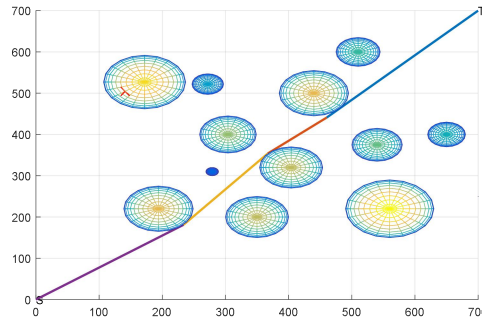


Figure 4: Two-dimensional sectional view.

The Figure 5 is a comparison of the optimization curves of the UAV path planning algorithm. The figures respectively reflect the evolution curves of the HBA and BA algorithms. From the figure, it can be intuitively analyzed that when the evolution algebra reaches about 18 generations, the HBA algorithm starts to converge and evolves. The area was stable around the 120th generation. However, the BA algorithm converges prematurely, resulting in premature maturity, which makes the accuracy of the solution lower, and the results have larger errors and lower credibility than the actual results.

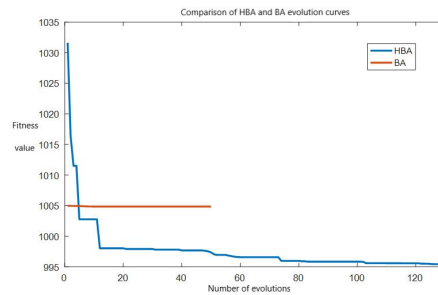


Figure 5: Comparison of HBA and BA evolution curves.

Table 2 shows the analysis of the fitness functions of the HBA and BA algorithms at different evolution times. Combined with the graph, it can be obtained that the HBA algorithm is more accurate in solving path planning, and effectively prevents the group from converging prematurely and falling into the local optimum Case.

Table 2: Comprehensive analysis of solution data.

Number of iterations	100		200		300		400	
	HBA	BA	HBA	BA	HBA	BA	HBA	BA
Best	1002	998	999	998	997	1004	996	1004
Worst	1040	1042	1034	1035	1021	1038	1028	1041
Mean	1016	1008	1015	1006	1022	1022	1007	1021
ζ	12.4	12.0	9.1	9.47	6.4	10.8	8.0	1.284

5. Conclusions

Based on the traditional BA algorithm, this paper uses the improved mutation mechanism to deal with the precocity of the population, and proposes a hybrid bat algorithm (HBA) that dynamically adjusts the step size, leading to a solution to the path planning of the UAV. The comparison of

simulation results shows that the improved bat algorithm shows a higher solution accuracy in the process of UAV track planning. Compared with the traditional BA algorithm, it greatly improves the problem of premature convergence of the group and makes the algorithm effective. Avoid getting trapped in a local optimum. However, because the mountain model proposed in this paper is based on the case that the base is round, the model is still too simple, and the actual situation is much more complicated, so the uncertainty of the model is reduced, so that the research is still in the theoretical part, and the actual effect is not outstanding. Therefore, how to enhance the uncertainty and diversity of the model is the content of subsequent research.

Acknowledgments

This work was funded by the key research and development project of Hainan Province of China (ZDYF2017066), the natural science foundation of Hainan Province of China (619MS028) and the Research on Education and Teaching Reform of Hainan University (hdjy1954).

References

- [1] Yang X S. A New Metaheuristic Bat- Inspired Algorithm[J]. *Computer Knowledge & Technology*, 2010, (284): 65- 74.
- [2] Ping Zhao, Degang Xu. Theoretical research on bat algorithm [J]. *Electronic Mass*, 2018 (09): 1-6.
- [3] Hua Xu, Bing Cheng. Hybrid genetic bat algorithm for single-objective flexible job shop scheduling problem [J]. *Small Microcomputer System*, 2018, 39 (05): 1010-1015.
- [4] Baolei Li, Danju Lu, Qinhu Zhang, Xinling Shi, Jianhua Chen, Yufeng Zhang. Path planning based on multivariate optimization algorithm.
- [5] Xiaomeng Li, Daobo Wang, Jikai Guo, Hua Yang, Bohang Wang. UAV track planning based on some biological heuristic algorithm [J]. *Mechanical & Electronics*, 2018, 36 (11): 15-19.
- [6] Chenyue Mao, Pengyong Wu. Obstacle avoidance algorithm for UAV path planning based on artificial potential field method [J / OL]. *Electronic Science and Technology*, 2019 (07): 1-7 [2019-01-12]. <http://kns.cnki.net/kcms/detail/61.1291.TN.20181220.0913.040.html>.
- [7] Yanyan Du, Sheng Liu. An improved adaptive hybrid bat algorithm [J]. *Microelectronics & Computer*, 2018, 35 (06): 135-140.
- [8] Shilei Lu, Yonglin Huang, Haiqiang Chen, Zhen Li, Weixing Wang. Improved bat algorithm based on adaptive step size [J]. *Control and Decision*, 2018, 33 (03): 557-564.
- [9] Haohao Cheng, Sen Yang, Xiaohui Qi. Four-rotor UAV track based on improved RRT algorithm [J]. *Computer Engineering and Design*, 2018, 39 (12): 3705-3711. Planning
- [10] Huiwen Zhan, Yabo Luo, Yuling Pan, Jian Xu, Yi He. Research on Multi-constrained Bilateral Assembly Line Equilibrium Problem Based on Hybrid Bat Algorithm [J / O]. *Industrial Engineering and Management: 1-10* [2019-01-12]. <https://doi.org/10.19495/j.cnki.1007-5429.2019.01.003>.
- [11] Qian Guo. Research on Vehicle Routing Problem Based on Improved Bat Algorithm [D]. Henan University, 2018.