Mathematical Modeling and Algorithm Application
ISSN: 3006-0842 | Vol. 3, No. 2, 2024

An Improved BSA with Dynamic Grouping Strategy and Its Application in UAV Path Planning

Zirui Zhao*

Xi'an Technological University, Xi'an 710021, China
* **Corresponding author**: zhaozirui@st.xatu.edu.cn

Abstract: Due to the issues of slow convergence speed and low accuracy in swarm intelligence algorithms for UAV path planning, this paper proposes An Improved Bird Swarm Algorithm with dynamic grouping strategy(DGSBSA).This method introduces strategies such as dynamic grouping and reverse foraging to enhance the algorithm's performance.During the iteration process, dynamic grouping is performed based on the positions of the bird swarm to enhance population diversity.The experimental results demonstrate that the proposed DGSBSA algorithm improves the algorithm's accuracy and enhances the convergence speed in the path planning process.

Keywords: DGSBSA algorithm, Path planning, Dynamic grouping, Reverse foraging, Convergence speed.

1. Introduction

With the rapid development of machine learning, deep learning, visual perception, and data fusion technologies, UAV technology has become a critical focus of military and technological competition in many countries.Path planning technology is one of the key technologies for enabling autonomous movement in robots, with unmanned intelligent devices completing both indoor and outdoor tasks through embedded path planning algorithms.

According to existing research on UAV path planning, the path planning problem for UAVs in complex environments is typically formulated as a discrete constrained optimization problem to ensure the feasibility of the flight path.However, the degree of discretization in the flight environment is difficult to control.A low degree of discretization may result in the omission of important map information, while a high degree of discretization may lead to an excessively large search space.In this case, the UAV path planning problem has been proven to be a challenging NP-hard problem [1], requiring effective algorithms to find the optimal flight path.Considering the variability of the environmental scenarios in which UAVs perform tasks, an improved Bird Swarm Algorithm with dynamic grouping strategy is proposed.

The remainder of this paper is organized as follows:Section 1 introduces UAV path planning algorithms; Section 2 analyzes the current research status of UAV path planning algorithms; Section 3 discusses the direction of algorithm improvements; Section 4 analyzes the experimental results; and finally, conclusions are drawn in Section 5.

2. Research Status

The earliest proposed Bird Swarm Algorithm, which lacks an inertia weight, is referred to as the initial Bird Swarm Algorithm.In 2016, literature [2] first introduced an inertia weight strategy to improve the Bird Swarm Algorithm. The inertia weight was added to the initial Bird Swarm Algorithm to modify the position update formula during foraging, allowing for better coordination between individual birds and the entire flock, which is beneficial for optimization.In literature [3], the Levy flight strategy was used to initialize the bird swarm positions in order to increase the diversity of the swarm and facilitate escaping local optima.In literature [4], the deficiencies of the Bird Swarm Algorithm were addressed, and the algorithm was improved through migration strategies and mutation methods, which enhanced its convergence efficiency.In literature [5], to address the issue of reduced diversity in the later stages of the Bird Swarm Algorithm, which leads to a tendency to fall into local optima, the black hole theory strategy was introduced to improve the algorithm.In literature [6], improvements were made to the algorithm's foraging behavior and other parameters, effectively enhancing the algorithm's optimization capability.

In summary, the research on the Bird Swarm Algorithm has made certain advancements in both algorithm theory and applications. However, the algorithm still has model deficiencies, a tendency to fall into local optima, and shortcomings in optimizing in dynamic environments.To address these shortcomings, this paper proposes DGSBSA. By employing dynamic grouping strategy, nonlinear control parameter strategy, and reverse foraging strategy, the defects of the Bird Swarm Algorithm (BSA) are resolved. Experimental results show that DGSBSA converges faster and performs better than both BSA and IBSA in the same environmental model.

3. The DGSBSA Algorithm

3.1. Problem Description

To enhance the precision of UAV path planning, we establish a continuous constrained optimization problem. Incorporating key elements like environmental conditions and UAV capabilities.

The *i-th* waypoint of the flight path is denoted $\mathrm{asp_i}$, and its coordinates are marked as(x_{pi}, y_{pi}, z_{pi}). Therefore, the flight path is represented as:

$$Path = [\overrightarrow{p_1 p_2}, \cdots, \overrightarrow{p_i p_{i+1}}, \cdots, \overrightarrow{p_{n-1} p_n}] \tag{1}$$

Where, *Path* represents the flight path, as shown in Figure 1, where p_1 and p_n denote the starting point and the target point, respectively. $\overrightarrow{p_i p_{i+1}}$ represents the vector segment from waypoint p_i to waypoint p_{i+1}.

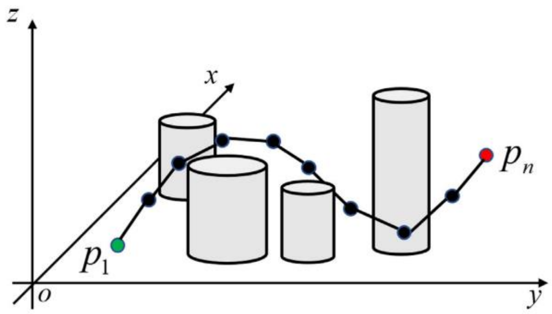

Figure 1. UAV Flight Path

In the optimization problem, the cost function of UAV path planning is associated with the energy consumption of the flight path and its feasibility.

$$Cost_L = \sum_{i=1}^{n-1} \|\overrightarrow{p_i p_{i+1}}\| \tag{2}$$

$$Cost_H = a_1 \sum_{i=1}^{n} \left|z_{pi} - h_{mean}\right| + a_2 \sum_{i=1}^{n} \left|z_{pi} - h_{limit}\right| \tag{3}$$

$$h_{mean} = \frac{1}{n} \sum_{i=1}^{n} z_{pi} \tag{4}$$

$$h_{limit} = (h_{max} - h_{min})/2 \tag{5}$$

Eq.(2) represents the displacement cost function.Eq.(3)-(5) represent the altitude cost functions.The total cost function is as follows:

$$TotalCost = \omega_1 Cost_L + \omega_2 Cost_H \tag{6}$$

In Eq.(6),where ω_1 and ω_2 are the weight factors; $Cost_L$ and $Cost_H$ are the length cost function and altitude cost function mentioned above, respectively.

3.2. DGSBSA

The proposed DGSBSA introduces dynamic grouping strategy, nonlinear control parameter strategy, and reverse foraging strategy based on the BSA.In subsequent iterations, through dynamic grouping, the definitions of the bird swarm's relative velocity and cohesion are established. The entire bird swarm is randomly divided into multiple subgroups, and the diversity of each subgroup in the optimization process is assessed and adjusted. This promotes information exchange between different groups. The dynamic grouping strategy occurs with a fixed probability.These operations increase the diversity of the population, helping it escape from local optima and enhancing its search capability. At the same time, they reduce the individual differences within the swarm, improving convergence accuracy.

3.2.1. Dynamic Grouping Strategy

To address the issue of the traditional Bird Swarm Algorithm easily falling into local optima, in DGSBSA, the entire bird swarm is randomly divided into H subgroups, with each subgroup consisting of K individuals. To enrich the diversity of the population, each subgroup uses its own individuals' information to find more promising foraging positions.

3.2.2. Nonlinear Control Parameter Strategy

A nonlinear control parameter based on the inverse sine function is introduced during the bird swarm foraging process to enhance the optimization ability of finding the global optimal solution.The parameter modeling is as follows:

$$shrink = 2 - \frac{4}{\pi} \cdot arcsin((\frac{t}{T_{max}})^2) \tag{7}$$

In Eq.(7),Where T_{max} represents the maximum number of iterations, and t represents the current iteration number.

3.2.3. Reverse Foraging Strategy

To increase the optimization efficiency of the bird swarm, the stagnation state of the swarm's convergence during iterations is measured by the multiple of the cohesion.The similarity $S_{i,z}$ between bird i and bird z, and the cohesion $c_n(t)$ at a certain time are defined as follows:

$$S_{i,z} = 1 - (x_{i,d} - x_{z,d})/max|ub - lb| \tag{8}$$

$$C_n(t) = \frac{1}{n} \sum_{i=1}^{n} S_{i,p} \tag{9}$$

Where μb and lb represent the upper and lower bounds of the search, respectively, and n represents the size of the bird swarm.

By combining the aforementioned nonlinear control parameter strategy and the cohesion of the bird swarm, the position update formula for the bird swarm foraging is adjusted as follows:

When $C_n(t) < \lambda C_n(1)$, the corresponding foraging position is:

$$x_{i,j}^{t+1} = shrink \cdot x_{i,j}^{t} + (p_{i,j} - x_{i,j}^{t}) \times C \times rand(0,1) + (g_j - x_{i,j}^{t}) \times S \times rand(0,1) \tag{10}$$

When $C_n(t) > \lambda C_n(1)$, the corresponding foraging position is:

$$x_{i,j}^{t+1} = shrink \cdot x_{i,j}^{t} - (p_{i,j} - x_{i,j}^{t}) \times C \times rand(0,1) - (g_j - x_{i,j}^{t}) \times S \times rand(0,1) \tag{11}$$

3.3. Summary of the DGSBSA Algorithm Steps

1.Initialize Parameters.

2.Dynamically group the bird swarm based on the dynamic grouping probability. Calculate the cohesion between individuals.

3.Execute the foraging strategy or reverse foraging strategy based on the cohesion.

4.Update the position and fitness of each individual.

5.Update the cost function calculation based on the updated positions.

6.Repeat steps 2-5 until the maximum number of iterations is reached, and output the final solution.

4. Simulation and Experimentation

4.1. Simulation

The simulation experiments in this paper were carried out in the Gazebo environment on an Ubuntu 22 system, with the 11th Gen Intel® Core™ i7 - 1165G7 processor being used. The experimental environment was carefully constructed and configured to ensure that the actual operation conditions of the UAV in real scenarios could be accurately simulated. During this process, we took into full consideration the impacts of various environmental factors, such as the potential interferences of wind speed, air pressure, etc. on the flight trajectory of the UAV. The experimental environment setup parameters are shown in Table 1.

Table 1. Threat Area Information

	Threat Center	*Threat Radius*	*Altitude*
Model 1	*(350,100)*	*80*	*1000*
	(200,600)	*150*	*800*
	(650,160)	*100*	*500*
	(450,800)	*75*	*1000*
	(680,400)	*70*	*500*
	(850,600)	*80*	*750*
	(150,260)	*100*	*200*
Model 2	*(50,200)*	*150*	*600*
	(380,500)	*150*	*800*
	(550,100)	*150*	*1000*
	(150,750)	*200*	*1000*
	(680,350)	*120*	*1000*
	(850,250)	*200*	*600*
	(450,700)	*150*	*600*

4.2. Analysis of Experimental Results

This paper primarily analyzes the algorithm from two aspects: the accuracy of the UAV path planning algorithm and the convergence of the algorithm.To demonstrate the advantages of the DGSBSA algorithm, this paper compares the performance of BSA, ABSA, GWO, HGS, and DGSBSA under the same conditions.The details of the comparison function parameters are shown in Table 2.

Table 2. Details of Comparison Function Parameters

Algorithm	*Parameter*
GWO	$a = [2,0]$
PSOGWO	$c_1 = c_2 = c_3 = [2,0]$; $\omega_{max} = 1$; $\omega_{min} = 0.5$
BSA	$C = S = 1.5$; $a_1 = a_2 = 1$; $p \in [0.7,0.9]$; $F_1 \in [0.5,0.9]$
ABSA	$C = S = 1.5$; $a_1 = a_2 = 1$; $p \in [0.7,0.9]$; $F_1 \in [0.5,0.9]$; $\tau \in [0.5,0.9]$
DGSBSA	$C = S = 1.5$; $a_1 = a_2 = 1$; $N = 6$; $p \in [0.7,0.9]$; $F_1 \in [0.5,0.9]$; $\lambda = 6.8$

Table 3. Algorithm Accuracy Results

	Mean				
Model	*GWO*	*PSOGWO*	*BSA*	*ABSA*	*DGSBSA*
1	*5.8455E -54*	*8.9738E -07*	*1.6217E -02*	*8.1861E -236*	*0.0000E + 00*
2	*- 9.8148E + 00*	*- 7.2683E + 00*	*- 9.9493E + 00*	*- 9.2310E + 00*	*– 1.0134E +01*
	Std				
1	*1.0813E +03*	*3.4257E + 03*	*7.8348E +02*	*1.2402E + 03*	*2.8955E + 01*
2	*5.9029E +02*	*3.0228E + 00*	*3.3248E + 00*	*2.1657E + 00*	*9.3076E -01*

Table 3 shows the mean and standard deviation results of the final algorithm accuracy for UAVs using different path planning algorithms under the same model. The comparison indicates that the improved method has lower values for both the mean and standard deviation, suggesting that the accuracy of the algorithm has been improved compared to other algorithms.

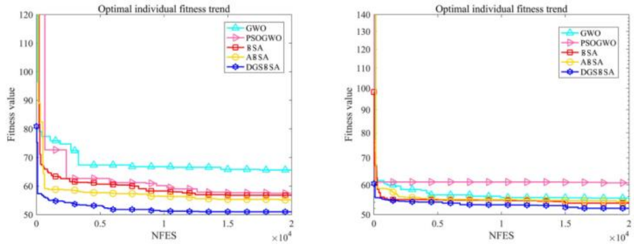

Figure 2. The convergence curve graphs of DGSBSA, BSA, ABSA, GWO, and PSOGWO

In Figure 2, the bottom curve represents the convergence speed of DGSBSA. The experiment shows that, compared to other path planning algorithms, the proposed algorithm demonstrates a significant improvement in convergence speed.

5. Conclusion

To address the issues of slow convergence speed and poor diversity in UAV path planning, this paper proposes an improved BSA algorithm (DGSBSA) that integrates a dynamic grouping strategy.By introducing a dynamic grouping strategy to improve population diversity, a nonlinear parameter control strategy to enhance convergence accuracy, and a reverse foraging strategy to accelerate convergence speed.The experimental results show that the proposed method not only improves algorithm accuracy but also enhances convergence speed, significantly increasing algorithm efficiency and the effectiveness of UAV path planning.

References

[1] Aggarwal, S, & Kumar, N. (2020). Path planning techniques for unmanned aerialvehicles: A review, solutions, and challenges. Computer Communications, 149, 270–299.

[2] Zhang Weiwei, Liu Yongjin, Peng Junjun. Improved Bird Swarm Algorithm for SVM Parameter Selection [J]. Computer Engineering and Design, 2017, 38(12): 3267-3278.

[3] Yang Wenrong, Ma Xiaoyan, Bian Xinlei. Adaptive Improved Bird Swarm Algorithm Based on Levy Flight Strategy [J]. Journal of Hebei University of Technology, 2017, 46(5): 10-22.

[4] Wang Jianwei, Peng Yigong. Improved Bird Swarm Algorithm with Migration and Mutation Strategies and Its Application in Parameter Estimation [J]. Journal of East China University of Science and Technology, 2018, 44(4): 617-624.

[5] Qu Chiwen, Fu Yanming, Luo Mingshan, Lin Chengde, He Wei. Bird Swarm Algorithm for Solving Flexible Job Shop Scheduling Problems [J]. Computer Engineering and Applications, 2018, 54(17): 249-257.

[6] Yang Wenrong, Ma Xiaoyan, Xu Maolin, et al. Research on Optimized Scheduling of Microgrid Grid Connection Based on Improved Bird Swarm Algorithm [J]. Electrical Engineering & New Technology, 2018, 37(2): 53-60