Application study of UAV path planning based on the balanced search factor artificial bee colony algorithm

Wenlong Hao*, Bo Luo, Zhiyuan Zhang
Army Aviation College, UAV Center, Beijing 101100, China
*Corresponding author e-mail: awenlongok2021@people.com.cn

Abstract. In this paper, aiming at the shortcomings of slow convergence speed and weak local search ability of traditional artificial bee colony algorithm in path planning, an artificial bee colony algorithm based on balanced search factor is proposed for UAV path planning. Using a search strategy based on balanced search factor, the depth search is carried out while maintaining a certain population diversity. The global search ability and local development ability are balanced, the average accuracy of path planning is improved, the robustness of path planning is enhanced, and the ability to obtain better path solutions is improved.

Keywords: artificial bee colony algorithm, the balanced search factor, path planning.

1. Introduction
Path planning is the core part of UAV mission planning, which aims to find the optimal flight path of UAV from the starting position to the target position in a given planning space and meets the constraints and performance indicators. In order to ensure the feasibility, security and optimality of the planning path, the platform mobility constraints must be considered. At present, the methods for solving UAV path planning include mathematical planning method, artificial potential field method, algorithm based on graphics and intelligent optimization algorithm. Traditional algorithms based on mathematical models, such as taboo, grid and artificial potential field methods, are difficult to achieve ideal results, with problems of poor robustness, accuracy and efficiency; a series of globally optimal group intelligence optimization algorithms such as artificial bee colony algorithm, particle algorithm based on simulation of social insect behavior are characterized by robustness, global optimization and good parallelism [1]. Therefore, this paper studies the problem of UAV path planning, improves the shortcomings of the algorithm, and introduces two balanced search factors to improve the solution satisfaction of UAV path planning.

2. Basic Artificial Bee Colony Algorithm
The inspiration of artificial bee colony algorithm is derived from the foraging behavior of natural bees. Bee colonies are composed of hiring bees, following bees and investigating bees. They cooperate with each other to find the best nectar source, namely to obtain the optimal solution. Due to its few parameters and strong adaptability, it is widely used in various fields [2].
The algorithm first initializes the initial solution \( (X_1, X_2, \cdots, X_n) = I(1, \cdots, SN) \), which represents the candidate location searched by the i bee in the space \((i = 1, \cdots, SN)\), and the number of hired bees is SN. Initialized as follows:

\[
X^j_i = X^j_{\text{min}} + \text{rand}(0,1) \ast (X^j_{\text{max}} - X^j_{\text{min}}), j = 1, \cdots, D
\]  

In the formula, \( X^j_{\text{min}} \) is the minimum feasible solution; \( X^j_{\text{max}} \) is the maximum value of the feasible solution; \( \text{rand}(0,1) \) is a random number between \((0,1)\); \( i \in \{1, 2, 3, \cdots, SN\} \), SN is the number of food sources, each solution is a D-dimensional vector.

During each iteration, the hired bees perform a cross and variation process, share information with a randomly selected companion, and utilize a new location \( x^j_i \) search to search at the current location.

\[
X^j_i = X^j_i + \text{rand}(-1,1) \ast (X^j_i - X^j_j)
\]  

In this equation, the first hired bee exchanges information with the k hired bee in the j element; \( j \) is a random integer of \((1, D)\), \( k \) is a random integer of \((1, SN)\), and satisfies the condition of \( k \neq i \). The evaluation function is used to evaluate the generated food sources. The evaluation function is:

\[
\text{fitness}(x) = \begin{cases} 
1 & f(x) \geq 0 \\
\frac{1}{1 + f(x)} & f(x) < 0 
\end{cases}
\]  

After cross-variation of employed bees, a greedy strategy was selected and if the new location \( x^j_i \) is better, the previous location would remain in the original location. After all the hired bees complete the search process, the hire bee will share the honey source information with the follow bee, follow the bee through formula (4) to select a hire bee to follow:

\[
P = \frac{\text{fitness}(i)}{\sum_{j=1}^{SN} \text{fitness}(j)}
\]  

Each followed bee chose a hired bee, when \( P \geq \text{rand}(0,1) \), the follower chooses the i hired bee and searches nearby:

\[
Y^j_i = x^j_i + \text{rand}(-1,1) \ast (x^j_i - x^j_i)
\]  

By using the greedy selection strategy again, if following the bee searches better than the hired bee, the hiring bee moves directly to that location or stays in situ.

During the iteration process, if a solution has a limit cycle and has not been further updated, then it is considered that the solution falls into local optimum, and the food source will be abandoned. Then the hired bee corresponding to this food source will be converted to the detection bee, and a new food source will be generated to replace it, and then return to the hired bee search process [3].

3. Improved Artificial Bee Colony Path Planning Algorithm

When modeling the motion space of the UAV, the following assumptions are made: the UAV moves in a two-dimensional finite space, and there are limited threat sources with known locations and threat distribution functions in the space. Ignoring the height change of the UAV, it is assumed to fly at a constant height. Then the path planning of UAV is to find a set of points \( P = \{S, Y_1, Y_2, \cdots, Y_n, E\} \) in the limited motion space, where S and E represent the starting point and end point respectively, and require the path cost between adjacent points to be minimal.

The traditional artificial bee colony algorithm has some problems in the search process, such as insufficient search depth, insufficient evolution of excellent individuals, and possible abandonment of the optimal nectar source. It is difficult to converge to the global optimal solution. In this paper, the global optimal solution of the current population is introduced into the search strategy of the follower bee. At the same time, in order to reduce the impact on population diversity, a search strategy based on
the balanced search factor is proposed to achieve the balance between global search ability and local development ability [4]. The neighborhood search formula of follower bees is as follows:

\[ X_j^{(t+1)} = X_j^t + \text{rand} \times (-1,1) \times (X_{best}^t - X_j^t) \times \varepsilon(t) + \text{rand} \times (-1,1) \times (X_j^t - X_i^t) \times \delta(t) \]  

\[ \varepsilon(t) = \log_2(1 + \frac{t}{T}) \]  

\[ \delta(t) = 1 - \varepsilon(t) \]  

In the formula, \(X_{best}^t\) is the j-dimensional element of the global optimal solution of the current population, \(\varepsilon(t)\) and \(\delta(t)\) are balanced search factors, \(t\) is the current iteration number, and \(T\) is the maximum iteration number. Obviously, at the beginning of the algorithm iteration \(\delta(t) > \varepsilon(t)\), the follower bee will have strong local search ability. In the middle and late iterations of the algorithm, the introduced optimal solution \(X_{best}^t\) of the current population retains the optimal honey source in the iteration process. The convergence speed is accelerated, while ensuring a certain global search ability to avoid falling into local optimum. The flow of the improved artificial bee colony algorithm is shown in Fig. 1.

The traditional bee colony algorithm only does neighborhood search for the current individual in the following bee neighborhood search stage, resulting in low efficiency and slow convergence speed. The method in this paper introduces the global optimal solution of the current population to accelerate the convergence rate, but it also leads to the lack of population diversity, which is prone to premature convergence or falling into local optimum. Therefore, in order to balance the global search ability and local development ability, we introduce the balance search factor \(\delta (t)\) and \(\varepsilon (t)\). In the early stage of evolution, \(\varepsilon < \delta\), the follower bee has strong local development ability; in the middle and late stages of evolution, \(\varepsilon > \delta\), the follower bee has strong local development ability, which greatly improves the performance of the algorithm.
4. Simulation Experiment

In order to verify the performance of the improved particle swarm algorithm, the proposed algorithm is compared with the traditional artificial bee colony algorithm in MATLAB environment. In the experiment, the parameters of the two algorithms are set as follows: the size of UAV flight space 120 * 120, the starting point (0, 90), and the end point (120, 90). According to the threat source model in [5], the number, type and location of threat sources are randomly generated. The number of individuals is 60, the number of honey sources is 30, the particle dimension $D=20$, the maximum stagnation $\text{limit} = 30$, and the maximum iteration $\text{MaxGeneration}=300$. The ABC algorithm and the IABC algorithm proposed in this paper are used for testing. The path planning results of the experiment are shown in Fig. 2. The curve of the fitness value changing with the number of iterations in the experiment is shown in Fig. 3.

![Figure 2. Path planning results](image)

![Figure 3. Target function convergence curve](image)
From the experimental results, the proposed search strategy based on balanced search factor effectively improves the convergence speed of the algorithm in the medium term, while ensuring the diversity of the population, avoiding premature, falling into local optimum, balancing the global search ability and local development ability, and the performance of the algorithm has been improved. The algorithm was run 50 times separately, and Table 2 records the optimal fitness value, average fitness value, worst fitness value, standard deviation of fitness value and average running time of the paths obtained by the two algorithms.

Table 1. Experimental results of fitness comparison of bee colony algorithm

| algorithm | Optimal values | Average  | The worst value | standard error | Run time   |
|-----------|----------------|----------|-----------------|----------------|------------|
| ABC       | 1.3805         | 1.4694   | 1.5359          | 0.0257         | 2.4399s    |
| IABC      | 1.3812         | 1.3842   | 1.4120          | 0.0135         | 2.4705s    |

5. Summary

From the comparison results of 50 experiments, the search results of the improved algorithm are significantly improved in the average search accuracy, and the optimal value and the worst value are also maintained at a better level, and the calculation time of the algorithm is not significantly increased. The artificial bee colony algorithm based on the balanced search factor proposed in this paper effectively improves the average accuracy of path planning, enhances the robustness of path planning, and improves the ability of the algorithm to obtain better path solutions, and it is easier to obtain satisfactory solutions in multiple repeated experiments.

When the dimension of the variable increases, the complexity of the problem increases exponentially, and the optimization difficulty of the algorithm increases, so the algorithm has defects in solving high-dimensional optimization problems. Therefore, how to make the algorithm solve complex problems is the next research work.

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