Obstacle Avoidance and Path Planning for Quadrotor based on Differential Evolution - Artificial Bee Colony Algorithm

Cheng Haohao, Qi Xiaohui, Yang Sen
Department of Unmanned Aerial Vehicle, Army Engineering University, Shijiazhuang 050003, China

Abstract. When the traditional artificial bee colony algorithm approaches the global optimal solution, the algorithm has the disadvantages of lower diversity, slower search speed, premature convergence, and trapping into local extremes. Based on the principle of differential evolution algorithm and combined with differential evolution algorithm, a differential evolution - artificial bee colony algorithm is proposed. Firstly, the global search ability of artificial bee colony algorithm is used to conduct global search. When approaching the global optimal solution, the diversity, crossover, and selection process of differential evolution algorithm is used to increase the diversity of solutions and avoid falling into local extremes. Finally, the differential evolution - artificial bee colony algorithm and differential evolution algorithm are compared in the urban environment model. The results show that the differential evolution - artificial bee colony algorithm is obviously superior to the other two algorithms in the quality and stability of path planning and obstacle avoidance for quadrotor.

1. Introduction
In recent years, bionic intelligence algorithms [1] such as particle swarm optimization, ant colony algorithm, genetic algorithm and artificial bee colony (ABC) algorithm have been widely applied to the path planning of quadrotor and robots. Among them, the artificial bee colony algorithm is a new swarm intelligence algorithm [2] that simulates bee honey collecting behavior. It has attracted attention due to its advantages such as simple structure, easy implementation, less control parameters, and simple calculation. However, in the solution process, defects such as premature convergence, low convergence accuracy, and slow convergence rate are easy to occur [3-6]. To solve these problems, the researchers proposed some improvements. For example, Banharnsakun [7] proposed a local search strategy that uses the current global optimal solution to adjust the neighborhood search step size to improve the convergence speed and optimization accuracy; Wang Bing [8] proposed a reverse learning strategy to initialize the population and a search strategy based on the current optimal solution to speed up the convergence of the algorithm. This improvement to a single algorithm had a certain limit to the performance improvement of the algorithm. Combining the two algorithms to achieve complementary advantages is another effective way to improve the performance of the algorithm [9].

Compared with the artificial bee colony algorithm, the differential evolution (DE) algorithm derives new populations through mutation, crossover, and selection operations, which helps the algorithm to jump out of the local optimal value, but it has the disadvantage of long computing time [10]. This paper combines the two algorithms and proposes a differential evolution - artificial bee colony (DE-ABC) algorithm. This algorithm not only overcomes the shortcomings of premature convergence, low convergence accuracy and slow convergence speed of the artificial bee colony...
algorithm, but also improves the computational speed of the differential evolution algorithm.

2. Track Cost
Cost function is the criterion for evaluating track quality, and it is also the basis for track optimization [11]. The design of the cost function directly determines the trajectory of the algorithm. In the track cost function of obstacle avoidance and path planning for quadrotor, two main indicators are considered: mobility cost and time cost.

2.1. Mobility Cost
In the offline obstacle avoidance path planning of the quadrotor UAV, the first consideration is the mobility cost of the trajectory. This is because the trajectory beyond the performance constraints of the quadrotor is an infeasible trajectory, and even if the mobility does not exceed the performance constraints of the quadrotor, tracks with tortuous track and poor smoothness are also not conducive to the flight of the quadrotor, which reduces the traceability of the quadrotor.

The cost of mobility can be expressed as:

\[
D(X) = \sum_{i=1}^{n+1} (k_\theta \theta_i + k_\phi \phi_i)
\]

\[
\theta_i = \arctan \left( \frac{-z_i}{\sqrt{x_i^2 + y_i^2}} \right) - \arctan \left( \frac{-z_{i+1}}{\sqrt{x_{i+1}^2 + y_{i+1}^2}} \right)
\]

\[
\phi_i = \arctan \left( \frac{y_{i+1}}{x_{i+1}} \right) - \arctan \left( \frac{y_i}{x_i} \right)
\]

In the formula, \( \theta_i \) represents the horizontal turning angle between the \(i\)th track segment and the \((i+1)\)th segment track segment; \( k_\theta \) is the horizontal turning angle coefficient; \( \phi_i \) is the pitch angle between the \(i\)th track segment and the \((i+1)\)th track segment of the quadrotor; \( k_\phi \) is the pitch angle coefficient; the vector coordinate of the \(i\)th track segment is \((x_i, y_i, z_i)\). From the above formula, it can be seen that the smoother the algorithm planning trajectory, the lower the maneuverability of the track.

2.2. Time Cost
Quadrotor flying along the planned track at a certain speed, the time used to avoid obstacles or reach the target point is closely related to the length of the planned track. The shorter the planned track is, the higher the timeliness is, and the shortest path length must be guaranteed to reduce the time cost.

The time-effectiveness cost can be expressed by the following formula:

\[
L(X) = k_2 \sum_{j=1}^{n+1} \left( L_j - \frac{l_0}{n+1} \right)^2
\]

Among them, \( k_2 \) denotes the aging index; \( L_j \) indicates the length of track segment in paragraph \(j\); \( l_0 \) denotes the straight distance from the starting point to the target point. It can be seen from (2) that when the track is a straight line between the starting point and the target point and the track point is evenly distributed on the whole track, the time cost of the track is \( L(X) = 0 \).

2.3. Track Cost Function
The track cost function can be expressed as the weighting of the maneuver cost and the time cost:

\[
J(X) = w_1 D(X) + w_2 L(X)
\]

Where \( J(X) \) is the cost function of the track \(X\); \( w_1 \) is the weighting coefficient of mobility; \( D(X) \) is the mobility cost of the track \(X\); \( w_2 \) represents the aging weighting coefficient; \( L(X) \) represents the time cost of the track \(X\). Since the quadrotor UAV can perform operations such as
hovering, the maneuverability has less constraints on the algorithm and greater timeliness constraints, so a smaller $w_1$ value and a larger $w_2$ value should be selected.

3. Artificial Bee Colony Algorithm and Differential Evolution Algorithm

3.1. Artificial Bee Colony Algorithm

ABC algorithm is a new group of intelligent optimization algorithm proposed by the Turkish scholar Karaboga D according to bee honey collection mechanism, and was introduced in China in 2008, which is a new type of global optimization algorithm [12].

In the ABC algorithm, bee colony activities consist of three parts: honey source, hire bee, and non-employee bee. The non-employed bee includes two kinds of individuals, the observation bee and the scout bee. The number of hired bees and observation bees accounted for half of the total bee colony. Employment bees correspond to the location of honey sources. In the path planning problem, the position of each honey source represents one track, and the honey content of the honey source corresponds to the fitness value of the track. The process of honeybee searching for the honey source is the process of the algorithm to find the optimal track [13]. For the optimized objective function $J(X)$, the artificial bee colony algorithm randomly generates $SN$ initial solutions $X_i (i = 1,2,…,SN)$, each of which is a D-dimensional vector. The hired bee conducts a global search to find the honey source, and randomly selects any one-dimensional component of the honey source to mutate according to formula (4):

$$v_{ij} = x_{ij} + \text{rand}(-1,1)(x_{ij} - x_{ij})$$

In the formula, $v_{ij}$ is the new honeypot location; $k$ and $j$ are all randomly selected, $i,k \in (1,2,…,SN)$, $j \in (1,2,…,D)$ and $k \neq j$; rand(-1,1) is a random number between (-1,1).

Hired bees determine the position of the new honey source according to the greedy method after they complete the mutation. If the fitness value of the new position corresponding to the honey source is higher than the fitness value of the honey source corresponding to the old position, the position is updated; otherwise, the old honey source is still kept unchanged and the honey source is continued to be mined. After the hiring bee completes the search, the honeybee information is passed to the observation bee, and selects the honey source $X_i$ according to the roulette method with the probability of $P_i$ in formula (5) and (6):

$$P_i = \frac{\text{fitness}(X_i)}{\sum_{s=1}^{SN} \text{fitness}(X_s)}$$

$$\text{fitness}(X_i) = \begin{cases} 1 & J(X_i) \geq 0 \\ 1 + |J(X_i)| & J(X_i) < 0 \end{cases}$$

In the formula, $P_i$ is the probability of selecting the $i$th track; $\text{fitness}(X_i)$ is the fitness value of the $i$th track; $J(X_i)$ represents the cost function.

In the ABC algorithm, the evolutionary stagnation threshold control parameter limit is an important parameter to determine whether the algorithm is stuck in stagnation. Executing limit loop on a solution $X_i$ does not improve its quality, the corresponding hired bee is converted to a scout bee and the scout bee generates a new solution from formula (7) instead of the original solution [14]:

$$x_i = x_{min} + \text{rand}(0,1)(x_{max} - x_{min})$$

Where: $x_{max}$ and $x_{min}$ are the upper and lower limits of the solution space, respectively.

3.2. Differential Evolution Algorithm

Differential evolution algorithm, proposed by Storn and Price of Berkeley University, is an optimization algorithm based on swarm intelligence, which guides the search process through the
cooperation and competition of individuals within a group. The unique memory ability of DE algorithm makes the algorithm can dynamically track the current search situation to adjust the search strategy, which has strong global convergence ability and robust performance.

The DE algorithm includes three processes: mutation, crossover and selection.

The mutation process fully utilizes the information of other individuals in the group, achieving the purpose of expanding the diversity of the population, and at the same time avoiding the randomness and blindness brought about by the mutation operation within the individual. The variation process formula is as follows:

\[ u_i = x_i + F(x_{r_1} - x_{r_2}) \] \hspace{1cm} (8)

Among them, \( u_i \) is a variation individual, \( x_{r_1}, x_{r_2}, \) and \( x_{r_3} \) are three different individuals selected from the population, and \( F \) is a scaling factor.

In order to increase the diversity of interference parameter vectors, the crossover operation shown in (9) is introduced:

\[
\begin{align*}
    w_{i,j} &= \begin{cases} 
    u_{i,j}, & \text{rand}(0,1) \leq CR \\
    x_{i,j}, & \text{rand}(0,1) > CR 
    \end{cases} 
\end{align*}
\] \hspace{1cm} (9)

In the formula, \( j=1,2,...,D \); \( D \) is the vector dimension, \( CR \in [0,1] \) is the crossover probability.

The differential evolution algorithm uses a greedy selection strategy to ensure that the next generation has the best objective function value. The selection formula is as follows:

\[
\begin{align*}
    x_{i+1} &= \begin{cases} 
    w_i, & J(w_i) < J(x_i) \\
    x_i, & J(w_i) \geq J(x_i) 
    \end{cases} 
\end{align*}
\] \hspace{1cm} (10)

4. Differential Evolution - Artificial Bee Colony Algorithm

ABC algorithm has fewer parameters and is easy to implement. It can effectively solve such complex optimization problems as path planning, but has the disadvantage of being trapped into local optimum. The DE algorithm derives new populations through mutation, crossover, and selection operations. After iteratively searching for optimal solutions, it has the disadvantages of complex and long computation time. In order to overcome the shortcomings of ABC algorithm and DE algorithm, ABC algorithm and DE algorithm are combined to form a DE-ABC algorithm. By parameter passing, the optimal path that satisfies the minimum cost function is planned in the fastest way.

The advantage of this combined algorithm is to make full use of the characteristics of both the ABC algorithm and the DE algorithm, which can improve the efficiency of the algorithm and optimize the track accuracy.

The ABC algorithm has the problem of lacking of development when searching in space using formula (4). For this purpose, the search strategy of formula (11) can be used instead of formula (4).

\[ v_g = x_g + \text{rand}(-1,1) \cdot (x_g - x_{kj}) + \text{rand}(-1,1) \cdot (x_{j,Global} - x_g) \quad k \neq j \] \hspace{1cm} (11)

In the formula, \( x_{j,Global} \) is the global optimal solution of the honey component. Since the new search strategy introduces the guidance of the optimal position, it can improve the development ability while guaranteeing the search capability.
5. Simulation Experiment

In order to verify the performance of the differential evolution artificial bee colony algorithm, 100 simulation experiments of the DE-ABC algorithm, ABC algorithm and DE algorithm were carried out in the urban space model of $200 \times 200 \times 50 (m^3)$. The track planning results are shown in Figure 1. The cost function values are shown in Table 1, and the cost function changes are given in Figure 2.

![Figure 1. Comparison of Planning Tracks](image)

It can be seen intuitively from Figure 1 that the DE algorithm has the most tortuous path and the longest track length, followed by the ABC algorithm. The DE-ABC algorithm is significantly superior to the previous two algorithms in planning the track. Figure 2 shows the change of the cost function during the planning process. In the initial stage, the value of the cost function of ABC algorithm decreases most quickly, and the algorithm has the strongest ability to search, but the search ability in the later stage is weakened and it is easy to fall into the local optimal value. DE algorithm has mutation, crossover, and selection operations, and the search results in the later stage are obvious. The DE-ABC algorithm is slower than the ABC algorithm in the initial stage but faster than the DE algorithm, but it is superior to the ABC algorithm and the DE algorithm in the convergence accuracy. This algorithm fully combines the advantages of the two algorithms and achieves a balance between convergence speed and convergence accuracy, which greatly improves the performance of the algorithm. The cost function values in Table 1 illustrate the performance of the three algorithms in more detail. The five indicators of the DE-ABC algorithm are the smallest, especially in terms of mean value and variance, which indicates the convergence precision and stability of DE-ABC algorithm are superior to the other two algorithms.
6. Conclusion
In this paper, the track cost function is firstly given; then the artificial bee colony algorithm and differential evolution algorithm are briefly introduced, and the advantages and disadvantages of the two algorithms are pointed out. According to the advantages and disadvantages of the two algorithms, a DE-ABC algorithm combined with the two algorithms is proposed. Finally, the traditional ABC algorithm, DE algorithm and DE-ABC algorithm are compared in the urban space model. The simulation results show that the DE-ABC algorithm has better convergence accuracy and stability, and the planning track is obviously better than the ABC algorithm and DE algorithm. So, it is more suitable for offline quadrotor obstacle avoidance and path planning.

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