Bat-Inspired Biogeography-Based Optimization Algorithm for Smoothly UAV Track Planning Using Bezier Function

Jingzheng Chong[1](✉), Xiaohan Qi[1], and Zhihua Yang[1,2]

[1] Communication Engineering Research Center, Harbin Institute of Technology
(Shenzhen), Guangdong, China
`{18s152591,qixiaohan}@stu.hit.edu.cn`, `yangzhihua@hit.edu.cn`
[2] Pengcheng Laboratory, Shenzhen, Guangdong, China

Abstract. With the extensive applications of Unmanned Aerial Vehicle (UAV), traditional approaches such as Artificial Potential Field and A-star for UAV track planning are usually limited by their low efficiency and easy failure, especially in the three-dimensional complex environments with obstacles. Moreover, most of these works do not make careful considerations on the fine-grain smooth of track requird heavily by the realistic flight of UAV. Therefore, in this paper, we propose an improved Biogeography-Based Optimization (BBO) algorithm with Bats algorithm (BA), named BIBBO for UAV track planning, which allows a new generating method with continuous Bezier curve by using adaptive-step sampling of control points to smooth original track. The simulation results verify the effectiveness and robustness of the proposed algorithm with shorter and smoother 3-D tracks, compared with typical BBO and BA algorithms.

Keywords: UAV track planning · BBO · BA · Track smoothing · Bezier curve

1 Introduction

In recent years, the UAV has played an increasingly important role in many fields including logistics, patrol and exploration due to its fast, flexible and high-efficiency. The UAV track planning in a known three-dimensional environment is the basis and prerequisite for a series of autonomous control activities of UAV assignment system such as formation control and multi-UAV coordination. However, the original tracks planned contains straight-line segments which generally cannot be followed well by UAV due to the kinematic and dynamic constraints. Therefore, UAV tracks must be smoothed by eliminating right-angled turns in order to make them suitable for UAVs. As discussed above, the track planning and smoothing are important research topics for UAV which received substantial attention.

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There are many traditional track planning methods. In [1], a new APF algorithm was put forward to promote UAV to get rid of the local minimum point. Chen et al. apply the A-star algorithm to UAV track planning under the two-dimensional environments in [2]. To avoid slow convergence and poor ability in high dimensional space, the algorithms based on swarm intelligence have attracted the attention of many scholars, including Ant Colony Optimization [3–5], Grey Wolf Optimization [6], Genetic Algorithm [7,8], Particle Swarm Optimization [9,10]. In addition, an improved Rapidly-exploring Random Tree algorithm is proposed in [11], but RRT is a random sampling-based method that doesn't guarantee to be optimal. BA was proposed first by Yang in 2010, which is inspired by the echolocation behavior of bats, and it is potentially more powerful than PSO and GA [12]. BBO algorithm was developed first by Simon in 2008 [13], as a population-based evolutionary algorithm original from the mathematics of biogeography. Upadhyay et al. used BBO algorithm to evaluate the shortest path between load and generating centers in the area [14]. In [15], the BBO algorithm is exploited on the joint transmitter and receiver AS problem. But as far as we know, BBO algorithm is not generally used in the track planning of UAV nowadays.

In order to smooth the track, several methods have been proposed in recent researches. In [16], a novel path smoothing extension is presented, which uses the geometry of hypocycloids to smooth out the sharp and angular turns of the track, but this method smooths leaves the straight paths intact. The quadratic Bezier curve was used for track planning of a UAV ensuring less computational load in [17], but it lacks flexibility since only three control points are used. Therefore, in this paper, a new optimization algorithm named BIBBO is proposed, which improves the BBO algorithm by changing the migration model and mixes it with the BA. The motivation of BIBBO is to address the problems of slow convergence and easy falling into local optimal solutions. Additionally, in order to smooth the original track, we put forward a adaptive-step sampling method to obtain control points for continuous Bezier curve, which can be applied flexibly in different complex scenarios.

The remainder of this paper is organized as follows. The system model and the problem of UAV track planning is introduced in the Sect. 2. Section 3 presents a new optimization algorithm to plan the track. Section 4 presents the idea and steps of the continuous Bezier curve generated by new sampling method. Finally, Sects. 5 and 6 summarize simulation results and research conclusions, respectively.

2 System Model and Problem Formulation

The primary work of track planning is to establish the model of UAV's flight environment. A feasible model of the environment information could improve the efficiency of track planning, and has good visibility in display. We divide the three-dimensional environment into 100 * 200 * 100 points with unit of meters. More points means more accurate of the environment description, then the planning result is more effective. But too many points will enlarge the workload greatly, which will also decrease the entire efficiency. Without loss of generality, the three-dimensional environment can be decomposed into two parts, free points set $\mathcal{F}$ and occupied points set $\mathcal{M}$ respectively. The schematic graph of the three-dimensional environment model is showed in Fig. 1, in which the blue parts are obstacles. $\mathcal{F}$ and $\mathcal{M}$ can be described as follows:

$$\mathcal{F} = \{(x_{F_1}, y_{F_1}, z_{F_1}), (x_{F_2}, y_{F_2}, z_{F_2}) \ldots (x_{F_m}, y_{F_m}, z_{F_m})\} \tag{1}$$

$$\mathcal{M} = \{(x_{M_1}, y_{M_1}, z_{M_1}), (x_{M_2}, y_{M_2}, z_{M_2}) \ldots (x_{M_n}, y_{M_n}, z_{M_n})\} \tag{2}$$

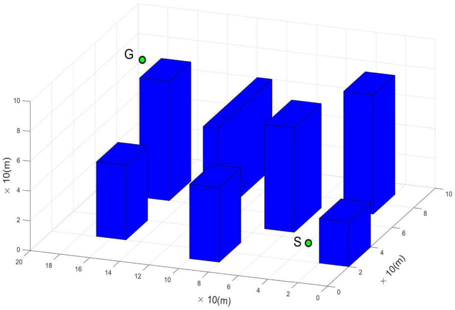


Fig. 1. Environment model (Color figure online)

We suppose that there are a starting point S and a goal point G in the three-dimensional environment as shown in Fig. 1. The optimal track planning is to find a collision-free and short track $\mathcal{T}$ that from S to G under the constrained dynamic properties of UAV flight system. We have two indexes to estimate a track: the length J_L and the hazard level J_R. Typically, these two indexes try to make the track as short as possible and the risk degree as lower as reasonable in the premise of completing the track planning. The definition of $\mathcal{T}$ and J_L can be expressed as follows:

$$\mathcal{T} = \{(x_{T_1}, y_{T_1}, z_{T_1}), (x_{T_2}, y_{T_2}, z_{T_2}) \ldots (x_{T_l}, y_{T_l}, z_{T_l})\} \tag{3}$$

$$J_L = \sum_{i=1}^{l-1} \sqrt{\left(x_{T_{i+1}} - x_{T_i}\right)^2 + \left(y_{T_{i+1}} - y_{T_i}\right)^2 + \left(z_{T_{i+1}} - z_{T_i}\right)^2} \tag{4}$$

For any given point $\mathcal{T}\{i\}(x_{T_i}, y_{T_i}, z_{T_i})$ in $\mathcal{T}$, d_i represents the minimum Euclidean distance from $\mathcal{T}\{i\}$ to the obstacles, which is defined in (5). Therefore, J_R can be described as Eq. (6).

$$d_i = \min\left\{\sqrt{\left(x_{T_i} - x_{B_j}\right)^2 + \left(y_{T_i} - y_{B_j}\right)^2 + \left(z_{T_i} - z_{B_j}\right)^2}\right\}, j \in [1, \mathrm{n}] \tag{5}$$

$$J_R = \sum_{i=1}^{l} \frac{1}{d_i} \tag{6}$$

As discussed above, it can be known that the tatal cost function of the track is based on the weighted indexes of the smallest length J_L and the least risk J_R. So we have:

$$J = \tau J_L + (1 - \tau) J_R \tag{7}$$

where J is the weighted sum of cost for the track; $\tau \in (0, 1)$ represents the weighting parameter. The choice of τ between 0 and 1 gives the designer certain flexibility to dispose relationships between the threat degree and the track length. When τ is closer to 1, a shorter track is planned with less attention paid to avoid obstacles. On the contrary, when τ is closer to 0, it requires avoiding the obstacles as far as possible on the cost of sacrificing the track length. Besides, we define d_c as the constraint of the track:

$$\begin{gathered} d_c(\mathcal{T}\{p\}, \mathcal{M}\{q\}) = \sqrt{\left(x_{T_p} - x_{M_q}\right)^2 + \left(y_{T_p} - y_{M_q}\right)^2 + \left(z_{T_p} - z_{M_q}\right)^2} \\ \text{for } \forall \mathcal{T}\{p\} \in \mathcal{T}, \forall \mathcal{M}\{q\} \in \mathcal{M} \end{gathered} \tag{8}$$

We assume the UAV flight safety radius of η. So the track planning problem can be described as:

$$\begin{aligned} &\min\ J = \tau J_L + (1 - \tau) J_R \\ &\text{s.t. } d_c(\mathcal{T}\{p\}, \mathcal{M}\{q\}) > \eta \end{aligned} \tag{9}$$

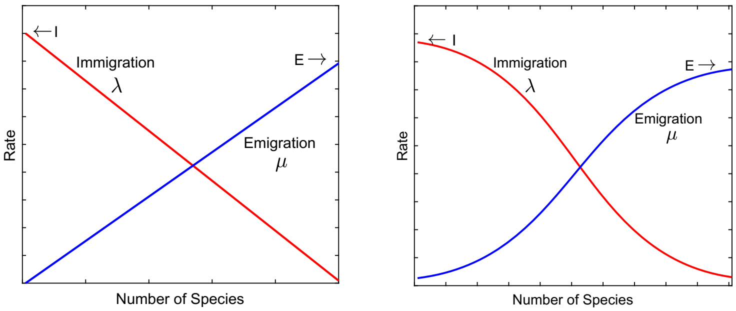
Additionally, in order to make this track meet the flight characteristics and dynamic constraints of the UAV, continuity and smoothness must be taken into account after planning so that the track could be feasible for the flight of UAV, which can be achieved by track smoothing. The detailed description is introduced in Sect. 4.

3 BIBBO Algorithm

The basic BBO algorithm treats every possible solution of the problem as a habitat, and sets the fitness of the each solution to the HSI (Habitat Suitability Index) of the habitat. Each solution is a vector constructed by feasible features called SIV (Suitability Index Variable). Migration process of BBO algorithm is used to replace feasible features in existing solutions, it is an adaptive process. The immigration rate λ and the emigration rate μ are functions of the number of species S in a single habitat as shown in Fig. 2(a). So we have:

$$\begin{cases} \lambda = I\left(1 - \dfrac{S}{S_{\max}}\right) \\ \mu = \dfrac{ES}{S_{\max}} \end{cases} \tag{10}$$

where E and I represent the maximum emigration rate and maximum immigration rate, respectively; S_{max} is the largest possible number of species that the habitat can hold.



(a) Linear model (b) Hyperbolic tangent curve model

Fig. 2. Migration model of a single habitat

But in general, the migration model may be more complicated. So we adjusted the migration model by the hyperbolic tangent function to more in line with the law of natural migration. Combining with (10), we can get the new migration model as follow:

$$\begin{cases} \lambda_{\text{new}} = \dfrac{I}{2}\left(-\dfrac{k^{S-\frac{S_{\max}}{2}} - k^{S+\frac{S_{\max}}{2}}}{k^{S-\frac{S_{\max}}{2}} + k^{S+\frac{S_{\max}}{2}}} + 1\right) \\ \mu_{\text{new}} = \dfrac{E}{2}\left(\dfrac{k^{S-\frac{S_{\max}}{2}} - k^{S+\frac{S_{\max}}{2}}}{k^{S-\frac{S_{\max}}{2}} + k^{S+\frac{S_{\max}}{2}}} + 1\right) \end{cases} \tag{11}$$

The hyperbolic tangent migration curve ($k = 1.4$) as shown in Fig. 2(b), we can see the trend of migration with the number of species is more moderate by using the hyperbolic tangent migration model. When a habitat has less or more species, the migration changes slowly, and moderate numbers of species can cause changes dramatically in migration.

However, the migration process of BBO algorithm is hard to maintain population diversity. Furthermore, the direction of the mutation is uncertain, so the new individual obtained by mutating are not always feasible. Therefore, convergence rate will decrease in the later stage of the BBO algorithm. The BA algorithm can update the solutions by using the historical information recorded and enhance the local search by generating a local new solution around the optimal solution. Introducing the BA update strategy during the migration process of BBO algorithm could improve the exploring ability, and maintain the diversity of the population in BBO algorithm well. The basic update strategy of BA algorithm can be expressed as:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\,\beta \tag{12}$$

$$v_i^t = v_i^{t-1} + \left(x_i^t - x^*\right) f_i \tag{13}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{14}$$

where $\beta \in (0,1)$ is a random number; x^* is the current global optimal solution; f_i is a frequency value between f_{min} and f_{max}. So we adjust the migration rule of BBO algorithm as follows:

$$v_i^t = v_i^{t-1} + \sigma_1 \left[J\left(H_i\right) - J\left(H_{index}\right)\right] f_i + \sigma_2 \left[J\left(H_i\right) - J\left(H_{best}\right)\right] f_i \tag{15}$$

$$H_{i\_}SIV_j = H_{index\_}SIV_j + v_i^t \tag{16}$$

where J is the total cost of track (habitat) introduced in (7); H_i, H_{index}, H_{best} are the immigrated habitat, the emigrated habitat and the optimal habitat after each iteration, separately; σ_i and σ_2 are constant coefficients. Besides, an optimization check is adopted to ensure the population is always evolving in a more optimized direction. We accept new solution only when the modified habitat H_{new} is better than the original habitat H_i. We transplanted the loudness A_i of bats in BA algorithm into habitats, which will be updated according to the Eq. (17) when a new better habitat is accepted.

$$A_i^{t+1} = \alpha A_i^t \tag{17}$$

where α is the attenuation coefficient of the loudness, and for any $0 < \alpha < 1$, we have:

$$A_i^t \rightarrow 0, \text{ as } t \rightarrow \infty \tag{18}$$

In addition, we learn from the local search part of BA algorithm to propose a elitism local walk approach, which is different from the general elitism strategy. The global optimal solution H_{best} is called the elite solution, which will be preserved temporarily in next migration process. Meanwhile, there will be a new solution H_{new} generated near H_{best} by Eq. (19), which will be used to replace the elite solution H_{best} only when it has lower total cost, otherwise we abandon it.

$$H_{\text{new\_best}} = H_{\text{best}} + \epsilon A^I \tag{19}$$

where $\epsilon \in (0,1)$ is a random number; A^I is the average loudness of all the habitats after I times iteration.

Suppose M, N represent the number of habitats and SIVs in one habitat, respectively. Based on the above improvements, we propose a new optimization algorithm named BIBBO, which can be expressed as Algorithm 1.

4 Track Smoothing

Since there are straight-line segments in the three-dimensional UAV track generated by BIBBO algorithm, the original track is usually not smooth. Taking into account the flight characteristics and dynamic constraints of the UAV, if the UAV's flight direction is changed with a large angle frequently, it will be difficult to control UAV stably, which will lead to the UAV hard to follow the track accurately. Therefore, before a track smoother is used to smooth the original track, it is not suitable for the UAV. In this section, a new generating method with Bezier curve is developed to smooth the original track.

Algorithm 1. The Process of BIBBO Algorithm

```
Begin
Initialize the $H_i$, $v_i$ and $A_i$, define the pulse frequency $f_i$
while less than the maximum iterations do
    for $i = 1$ to $M$ do
        Select $H_i$ with probability $\lambda_{new}$
        for $j = 1$ to $N$ do
            Select $H_{index}$ with probability $\mu_{new}$
            Change the $H_i\_SIV_j$ by equation (16) to generate $H_{new}$
            if $H_{new}$ is better than $H_i$ then
                Accept the new solution and increase $A_i$
            end if
        end for
    end for
    Execute elitism local walk strategy
end while
End
```

4.1 General Bezier Curve Track Smoothing

Bezier curve is a kind of smooth continuous spline curve. In particular, the basic n-order Bezier curve is defined as:

$$P(t) = \sum_{i=0}^{n} B_{n,i}(t) P_i, t \in [0,1] \tag{20}$$

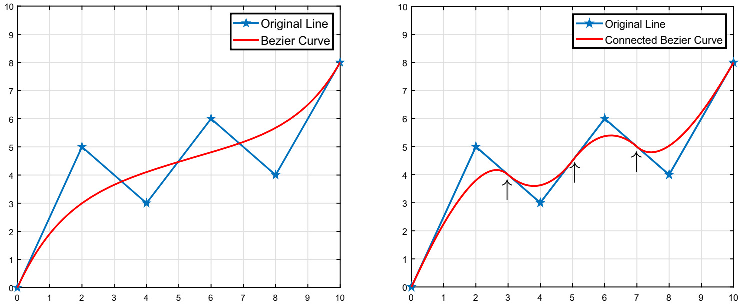
where P_i represents the coordinates of the i-th control point; $B_{n,i}(t)$ is the Bernstein function of degree n defined as follow:

$$B_{n,i}(t) = \binom{n}{i} t^i (1-t)^{n-i}, i = 0, \ldots, n \tag{21}$$

As shown in Fig. 3(a), the Bezier curve is surrounded completely by the convex hull that built by its control points, as is also applicable in three-dimensional environment. Since the UAV does not have to fly over each control points, so the track smoothed by Bezier curve is feasible.

Recently, track smoothing is mainly achieved by connecting multiple low order Bezier curves. As the Fig. 3(b) shows, a smooth track can be spliced by four two-order Bezier curves. Evidently, it has larger length and more sharp turns compared to the continuous Bezier curve created directly with 6 control points in Fig. 3(a).

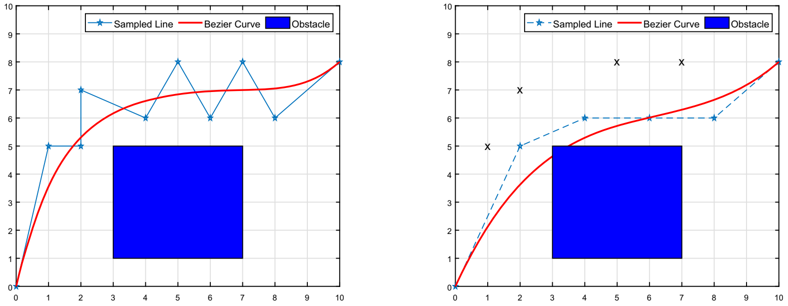
Based on the above analysis, it seems that smoothing track by using a continuous Bezier curve is perfect. But the original track is just a poly-line with many redundant points. More control points means higher order of Bezier function and involves more time to calculate or collision check. Since the Bezier curve is only determined by its pivotal control point, we don't need too many extra points to achieve track smoothing. By deleting redundant points, the computing speed



(a) Continuous Bezier curve (b) Spliced Bezier curve

Fig. 3. Bezier curves with different generating methods

will be greatly improved. However, there is no free lunch. Fewer control points may lead the smoothed track to pass through the edge of the obstacles as showed in Fig. 4.



(a) 10 control points (b) 6 control points

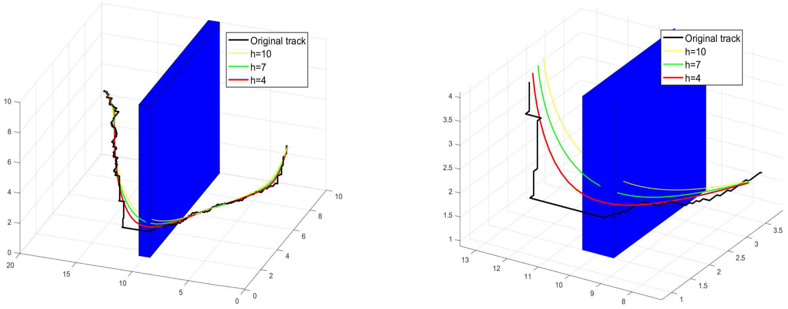
Fig. 4. Comparison of Bezier curves in a same environment

4.2 Bezier Curve with Adaptive-Step Sampling

In order to balance the computing performance and security, so in this section, a new generating method with Bezier curve by using adaptive-step sampling is developed to smooth track. The control points set $\mathcal{B}$ is created by sampling from the $\mathcal{T}$, and then it will be used to generate a Bezier curve which represents the smooth track. The sampling step size h can be adjusted from large to small. The initial value of the step size h generally depends on the complexity of the environment. The Algorithm 2 followed will shows the whole process of this method.

Algorithm 2. Bezier Curve Generating by Adaptive-Step Sampling

```
Begin
Set $flag = 1$, initialize step $h_0$
while ($flag = 1$) do
    $m = floor(n/h_0)$
    for $i = 2$ to $m$ do
        $j = i*m$; $\mathcal{B}\{i\} = \mathcal{T}\{j\}$
    end for
    $\mathcal{B}\{1\} = \mathcal{T}\{1\}$; $\mathcal{B}\{m+1\} = \mathcal{T}\{m\}$
    if $\mathcal{B}$ is collision free then
        $flag = 0$
    else
        $\mathcal{B} = \emptyset$; Adjust step to a smaller value
    end if
end while
Using $\mathcal{B}$ to generate Bezier Curve by equation(20)
End
```



(a) The global view (b) The partial enlarged view

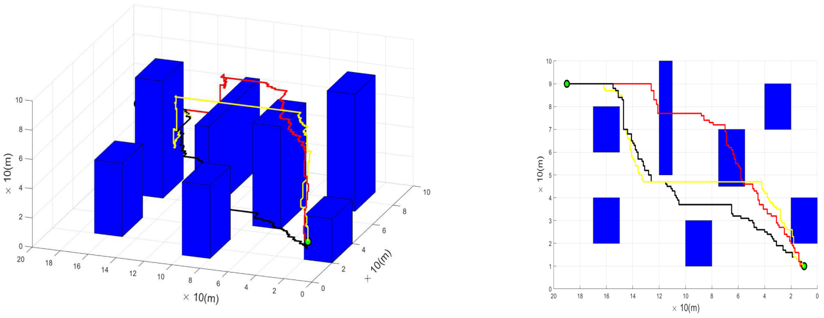
Fig. 5. Track smoothing by adaptive-step sampling

Figure 5 shows the results of track smoothing by adaptive-step sampling in a three-dimensional environment. From the perspective of a partial enlargement in Fig. 5(b), we can see clearly that when the step h is reduced to 4, the smoothed track no longer passes through the obstacle. This proves that the method which obtain control points by adaptive-step sampling to generate continuous Bezier curve is effective and flexible.

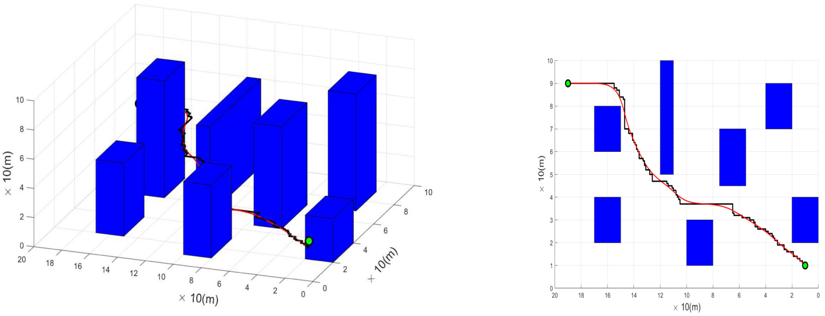
5 Experimental Results

In this section, simulations were designed to prove the efficiency of the approach proposed for UAV smooth track planning in the three-dimensional environment. In order to eliminate the effects of a specific environment, we used two maps of different complexity, each of which was repeated 30 times experiments. All simulations were programmed in a computer running Windows 10 with Intel

Core I3-6100 CPU @3.70 GHz. We set the starting point of (10, 10, 10), and the goal point of (90, 190, 40). The maximum immigration rate I and emigration rate E are both l. The maximal generation is 50, and the population size is 30. The initial sampling step h_0 is 10.



(a) Global view for original tracks (b) Top view for original tracks

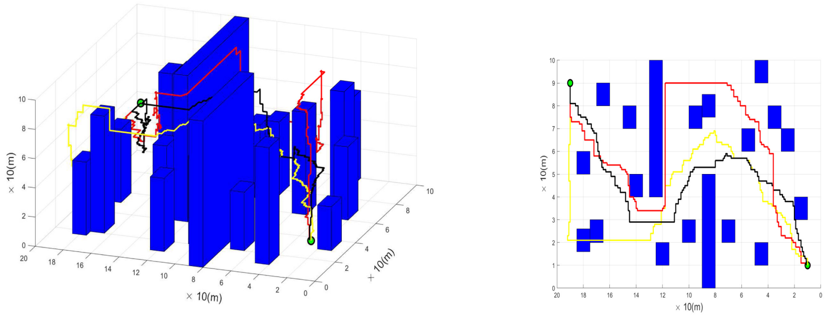


(c) Global view for smoothing (d) Top view for smoothing

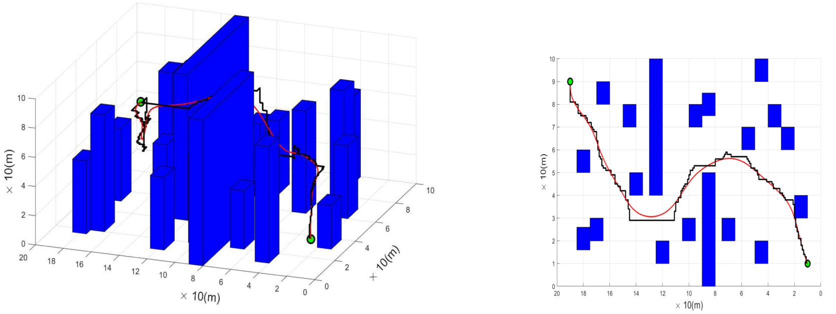
Fig. 6. Simulation results of simple map A (Color figure online)

Table 1. The length costs of three algorithms in simple map A

Algorithm	Mean	Std	Best	Worst
BIBBO	285.24	1.94	282.52	289.37
BA	293.35	17.80	286.95	335.84
BBO	298.67	8.08	289.13	316.23



(a) Global view for original tracks (b) Top view for original tracks



(c) Global view for smoothing (d) Top view for smoothing

Fig. 7. Simulation results of complex map B (Color figure online)

Table 2. The length costs of three algorithms in complex map B

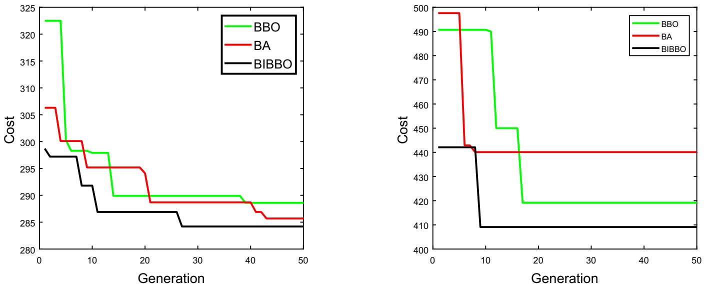
Algorithm	Mean	Std	Best	Worst
BIBBO	413.49	3.62	408.64	421.75
BA	467.13	34.39	415.78	532.22
BBO	437.33	9.17	419.85	454.56

Figure 6 shows the simulation results of simple map A. In Fig. 6(a) and (b), the line in green, red and black are the original track generated by BBO, BA and BIBBO algorithm separately. Similarly, the simulation results of complex map B are shown in Fig. 7. We can roughly see that the track created by BIBBO algorithm has fewer turns and is shorter than that of the other two algorithms. The detailed comparison of these tracks will be given in the Table 1 and Table 2. Besides, Fig. 6(c)(d) and Fig. 7(c)(d) show that the track (in red) generated by adaptive-step sampling is always smooth and safe even in a complex environment. Besides, the smooth track is very similar with the original track in shape.

According to Table 1 and Table 2, it can be concluded that the track length costs of BIBBO algorithm is always lower than BA and BBO algorithm.

In addition, the standard deviation of BIBBO algorithm is much smaller than that of the other two algorithms, which indicates obviously that the BIBBO algorithm is more stable in different environments.

Figure 8 shows the convergence comparison of the three algorithms, it can be observed that BIBBO algorithm has the faster convergence speed and lower cost compared with the other two algorithms.



(a) In simple map A

(b) In complex map B

Fig. 8. The convergence of three algorithms in different maps

6 Conclusion

In this paper, we propose an improved BBO algorithm with BA algorithm for UAV track planning, and a new generating method with continuous Bezier curve by using adaptive-step sampling of control points to smooth original track. Simulation results show that our approach can obtain better UAV smooth tracks in different three-dimensional environments. Simultaneously, the effectiveness and robustness of the proposed algorithm is also proved. In the future research we plan to improve the algorithm to work in the environment with dynamic obstacles.

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