2013 10th IEEE International Conference on Control and Automation (ICCA)
Hangzhou, China, June 12-14, 2013

Chaotic Differential Evolution Approach for 3D Trajectory Planning of Unmanned Aerial Vehicle

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Abstract — To overcome the disadvantage of low convergence speed and the premature convergence of differential evolution (DE), a chaotic DE was proposed. Aimed to improve the ability to break away from the local optimum and to find the global optimum, the non-winner particles were mutated by chaotic search and the global best position was mutated using the small extent of disturbance according to the variance ratio of fitness. Series of experimental comparison results are presented to show the feasibility, effectiveness and robustness of our proposed method. The results show that the proposed algorithm can effectively improve both the global searching ability and much better ability of avoiding pre-maturity.

I. INTRODUCTION

Trajectory planning for unmanned aerial vehicle (UAV) is one of the most important parts of mission planning. Trajectory planning is to generate a trajectory between an initial prescribed location and a desired destination having an optimal or near-optimal performance under specific constraints [1]-[3]. Research on UAV can directly affect battle effectiveness of the air force, therefore is crucial to safeness of a nation. Trajectory planning is an imperative task required in the design of UAV, which is to search out an optimal or near-optimal flight trajectory between an initial location and the desired destination under specific constraint conditions [2]. In recent years, some bio-inspired intelligent methods have emerged, which are definitely different from the classical mathematical programming principle. The typical bio-inspired methods include genetic algorithms (GAs), ant colony optimization (ACO), particle swarm optimization (PSO), artificial immune system (AIS), artificial bee colony (ABC), cultural evolution (CE), emotion computing (EC), and DNA computing. All the bio-inspired intelligent methods are trying to simulate the natural ecosystem mechanisms, which have greatly enriched the modern optimization techniques, and provided practical solutions for those complicated combinatorial optimization problems [4].

DE was originally presented by Storn and Price in 1995, and it has the advantages of strong robustness, good distributed computing mechanism, and easy to combine with other methods[5]. And the convergence speed and the stability have exceeded other stochastic algorithm, like annealed nelder and mead strategy (ANM), adaptive simulated annealing (ASA), evolution strategies (ES), stochastic differential equations (EDE). However, it can easily trap into the local best, hence would probably end up without finding a satisfying trajectory. Considering the outstanding performance of chaos theory in jumping out of stagnation, we introduced it to improve the robustness of basic DE algorithm, and the comparative experimental results testified that our proposed method manifests better performance than the original DE algorithm.

The remainder of this paper is organized as follows. Section 2 introduced the threat resource and objective function in UAV trajectory planning. Section 3 described the principle of basic DE algorithm, while Section 4 specified implementation procedure of our proposed chaotic DE algorithm. Then, in Section 5, series of comparison experiments are conducted. Our concluding remarks are contained in the final section.

II. ENVIRONMENT MODELING FOR UAV TRAJECTORY PLANNING

A. Threat sources in trajectory planning

Modeling of the threat sources is the key task in UAV optimal trajectory planning. There are two kinds of threat sources: artificial threats and natural threats. The artificial threats include the enemy's radar, missiles and artillery and so on [6]. We can choose appropriate models of them under different circumstances. In our model, we use the circle model to describe these threat sources, and the radius of the circle is the range of threat source, and we also can define the treat level to calculate the threat cost.

Mathematically, the problem of 3-D trajectory planning for UAV can be described as follows [7]:

Given the launching site A and target site B, ($A,B \in \mathrm{R}^3$), K threat sets { T_1, T_2, . . . , T_k }, and the parameters of UAV's maneuvering performance constraints (such as the

*This work was partially supported by Natural Science Foundation of China (NSFC) under grant #61273054, Program for New Century Excellent Talents in University of China under grant #NCET-10-0021, and Aeronautical Foundation of China under grant #20115151019, and YUYUAN Science and Technology Innovation Foundation for Undergraduate of Beihang University.

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restrictions of turning angle α, climbing/diving angle β, and flying height h, etc.), find a set of waypoints $\{W_0, W_1, \ldots, W_n, W_{n+1}\}$ with $W_0 = A$ and $W_{n+1} = B$ such that the resultant trajectory is safe and flyable. In other words, for the reported trajectory, no line segment intersects the interior of any T_1, T_2, . . . , T_k and all constraints are satisfied.

B. The performance evaluation function of trajectory optimization

Suppose that the terrain of the environment and the information of threat regions are known, and the start and aim points are also given. So we may obtain a high-quality flight trajectory between the start and aim points for UAV. And the cost function of flight trajectory can be defined as follows [8]:

$$F = w_1 f(l) + w_2 f(h) + w_3 f(c) \tag{1}$$

where w_1, w_2 and w_3 are weight coefficient, and they satisfy $w_1 + w_2 + w_3 = 1$.

For the given trajectory, the length cost $f(l)$ is define as:

$$f(l) = \sum_{i=1}^{n} l_i^2 \tag{2}$$

where l_i is the length of the ith trajectory segment.

The height cost $f(h)$ is define as[9]:

$$f(h) = \sum_{i=1}^{n} h_i \tag{3}$$

where h_i is the average altitude above the sea level of the ith route segment which minimizes the aircraft's altitude.

The threat cost $f(c)$ is computed by using the follow rules. While the UAV is in trajectory $L_{i,j}$, to simplify the calculation, we divide the trajectory $L_{i,j}$ into 5 sections, then the treat cost is[4]:

$$f(c) = \begin{cases} 0 & R_{ij} > R_j \\ \dfrac{L_{ij}}{5} \sum_{k=1}^{N_t} t_k \left(\dfrac{1}{d_{0.1,k}^4} + \dfrac{1}{d_{0.3,k}^4} + \dfrac{1}{d_{0.5,k}^4} + \dfrac{1}{d_{0.7,k}^4} + \dfrac{1}{d_{0.9,k}^4} \right) & R_{ij} \le R_j \end{cases} \tag{4}$$

where L_{ij} is the length of $L_{i,j}$, t_k is the kth treat level, R_j is the radius of the jth threat, N_t is the number of the threat, R_{ij} represents the average distance between the ith trajectory segment and the jth threat, $d_{0.1,k}$ is the length of the 1/10 point and the kth threat center[5]. By controlling the threat cost defined here, the survival probability of UAV can be increased effectively.

III. PRINCIPLES OF THE BASIC DE ALGORITHM

DE was first proposed by Ken Price's and Rainer Storn in 1995 for solving the Chebychev Polynomial fitting Problem. Since this seminal idea a lively discussion between Ken and Rainer and endless ruminations and computer simulations on both trajectories yielded many substantial improvements which make DE the versatile and robust tool it is today.

The basic operation include mutation operation, interleaving operation and selection operation [5].

A. Mutation Operation

Mutation operation is the main difference from DE and GA, in DE, the generation of mutation individuals used the father generation's linear combination. For any object vector x_i in the father generation, DE can generate the mutation vector v_i using the following formula:

$$v_i = x_{r_1} + F(x_{r_2} - x_{r_3}), \qquad i = 1, 2, \ldots, NP \tag{5}$$

where $\{x_{r_1}, x_{r_2}, x_{r_3}\}$ is three different individuals in father generation that satisfy $r_1 \ne r_2 \ne r_3 \ne i$, and NP is population size which is larger than 4, F is a scaling factor that lies between 0 and 2.

B. Crossing Operation

The aim of crossing operation is to recombinant the mutation vector v_i and object vector x_i to improve the diversity of the population. Using the following formula to generate a new crossing vector $u_i = [u_{i,1}, u_{i,2}, \ldots, u_{i,D}]$:

$$u_{i,j} = \begin{cases} v_{i,j}, & randb \le CR \quad or \quad j = rand_j \\ x_{i,j}, & randb > CR \quad or \quad j \ne rand_j \end{cases} \tag{6}$$

$$i = 1, \ldots, NP, \; j = 1, \ldots, NP$$

where $randb$ is the random number from 0 to 1, CR is crossing constant from 0 to 1, $rand_j$ a random integer from 1 to D.

C. Selection Operation

The selection operation is a greedy selection model, if and only if the fitness of the new vector u_i is better, it can be accepted. Otherwise, x_i is still retention to next generation. The selection operation can be described as follow:

$$x_i^{t+1} = \begin{cases} u_i, & f(u_i) < f(x_i^t) \\ x_i^t, & others \end{cases} \tag{7}$$

IV. PRINCIPLES OF THE CHAOTIC ALGORITHM

Chaos is the highly unstable motion of deterministic systems in finite phase space which often exists in nonlinear systems. Chaos theory is epitomized by the so-called 'butterfly effect' detailed by Lorenz. Attempting to simulate numerically a global weather system, Lorenz discovered that minute changes in initial conditions steered subsequent simulations towards radically different final stales, rendering long-term prediction impossible in general. Until now, chaotic behavior has already been observed in the laboratory in a variety of systems including electrical circuits, lasers, oscillating chemical reactions, fluid dynamics, as well as computer models of chaotic processes[10]. Chaos theory has been applied to a number of fields, among which one of the most applications was in ecology, where dynamical systems have been used to show how population growth under density dependence can lead to chaotic dynamics. Sensitive dependence on initial conditions is not only observed in complex systems, but even in the simplest logistic equation. In the well-known logistic equation:

$$x_{n+1} = 4x_n(1-x_n) \tag{8}$$

where $0 < x_n < 1$, a very small difference in the initial value of x would give rise to large difference in its long-time behavior, which is the basic characteristic of chaos. The track of chaotic variable can travel ergodically over the whole space of interest. The variation of the chaotic variable has a delicate inherent rule in spite of the fact that its variation looks like in disorder. Therefore, after each search round, we can conduct the chaotic search in the neighborhood of the current optimal parameters by listing a certain number of new generated parameters through chaotic process. In this way, we can make use of the ergodicity and irregularity of the chaotic variable to help the algorithm to jump out of the local optimum as well as finding the optimal parameters. The experimental results in Section 5 show the efficiency of our algorithm.

V. CHAOTIC DE APPROACH FOR SOLVING THE TRAJECTORY PLANNING PROBLEM

Due to the flexibility, versatility and robustness in solving optimization problems, DE algorithm has already aroused intense interest. However, there still exist some flaws on this algorithm, such as the local search ability is existing defect. In order to overcome these flaws of DE and upon the merits of chaotic variable, chaotic DE, which integrates DE with chaotic variable, was proposed in our work. After once iteration calculation, a good solution is produced, then conduct the chaotic search in the neighborhood of current best solution in order to choose one better solution into next generation. By this way, we can avoid from the local best, as well as to increase the speed of reaching the optimal solution. The implementation procedure of our proposed chaotic DE approach to UAV trajectory planning can be described as follows:

Step 1: According to the environmental modeling in Section 2, initialize the terrain information and the threaten information including the coordinates of threat centers, threat radiuses and threat levels.

Step 2: Initialize the parameters of DE algorithm, such as solution space dimension *D*, the population size *NP* , scaling factor *F* and crossing constant *CR*. Generally, a larger *NP* will contribute to a larger possibility of finding the best solution of the problem, however, it also means an increased computing complexity of the algorithm. In general, we define *NP = (3~10)D*. A smaller *F* will cause premature convergence, while a lager F will contribute to improving the capacity of jumping out of the local best, however, when *F*>1, the convergence speed will decrease, so we usually make *F* between 0.5 and 0.9[5]. A large crossing constant will accelerating convergence, normally, we choose *CR* between 0.3 and 0.5.

Step 3: Stochastic generate *N* trajectories and according to the parameters, calculate the cost of each trajectory formed by relative parameters based on formulas (1)–(4), then we get *N* feasible solutions.

Step 4: For the population of *N* feasible solutions, performing mutation operation using the formulas (5).

Step 5: For the new individual and the old individual, perform crossing operation using the formulas (6) to get the new individuals, meanwhile calculate the cost of the new individuals based on formulas (1)–(4). Then compare the cost of the target individuals and the new individuals, selecting the best get into next generation.

Step 6: Conduct the chaotic search around the best solution parameters based on formula (8) after transforming the parameters ranges into (0, 1). Among the engendered series of solutions, select the best one and use it to replace the former best solution.

Step 7: Store the best solution parameters and the best cost value.

Step 8: If *Nc* < *Nc*max, go to Step 4. Otherwise, output the optimal parameters and optimal cost value.

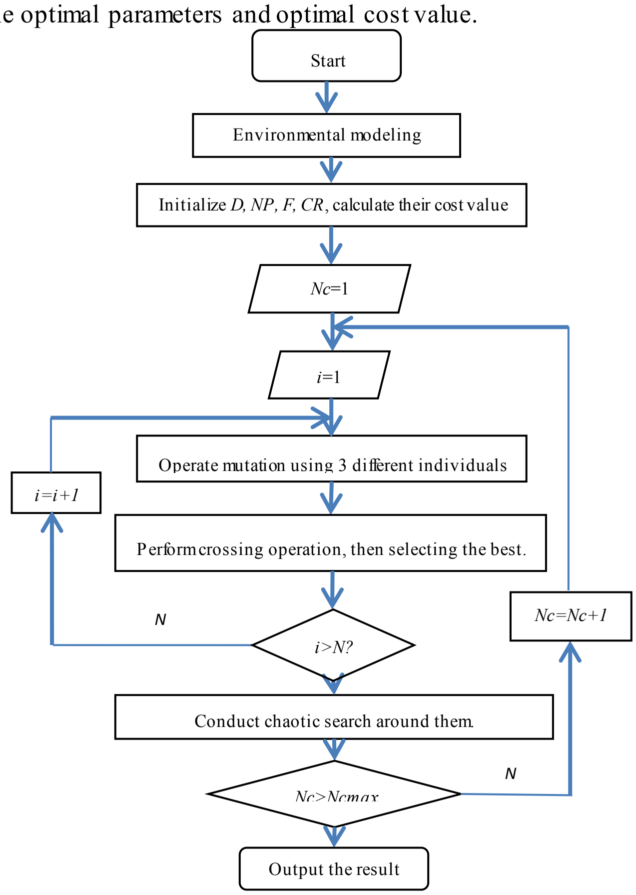

Fig. 1 The procedure of our proposed method

VI. EXPERIMENTAL RESULTS

In order to investigate the feasibility and effectiveness of the proposed method in this work, series of experiments are conducted, and further comparative experimental results with the standard DE algorithm are also given. Set the coordinates of the starting point as (0, 0, 30), and the target point as (65, 100, 30), while the initial parameters of DE algorithm were set as: NP = 60 , $Tmax$ = 200, F= 0.5, CR=0.9. Assume D as 20 to carry our experiments, the results of which are shown in Figs.1-7 is the trajectory planning result of chaotic DE algorithm.

The experimental results of standard DE and chaotic DE shown in Fig.1 and Fig.2 have differences due to the calculating complexity.

The simulation results can be shown in Figs. 4-7, which show the 3D trajectory planning result of the algorithm. Fig.4 is the vertical view of the trajectory planning, Figs.5-7 is the side views from different angles. The figures show our approach is feasibility.

From the above experimental results, we can clearly see that using standard DE algorithm could possibly lead to a trajectory that does not satisfy the requirements. Therefore, we make use of the ergodicity of chaotic variable to help the basic DE algorithm to jump out of the local best and obtain a favorable trajectory.

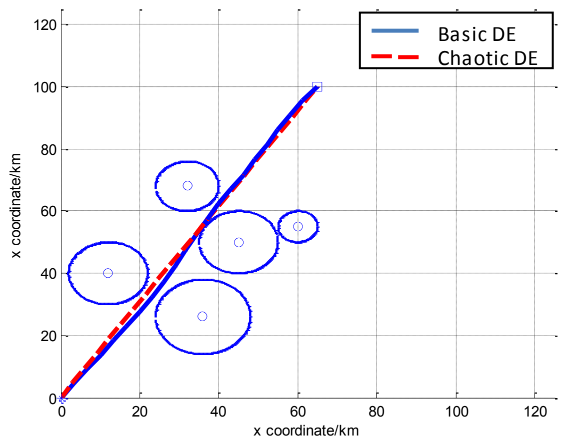

Fig. 2 The trajectories of two algorithms in x-y plane

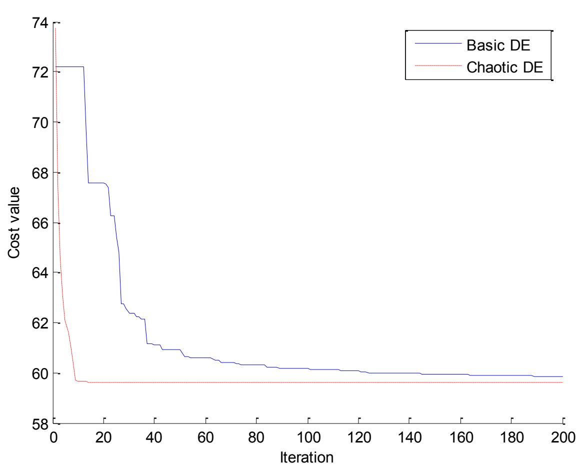

Fig.3 The evolution curves of two algorithms

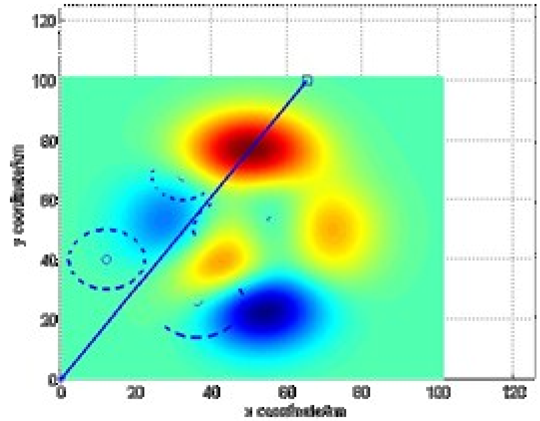

Fig.4 The 3D trajectory planning result of the algorithm

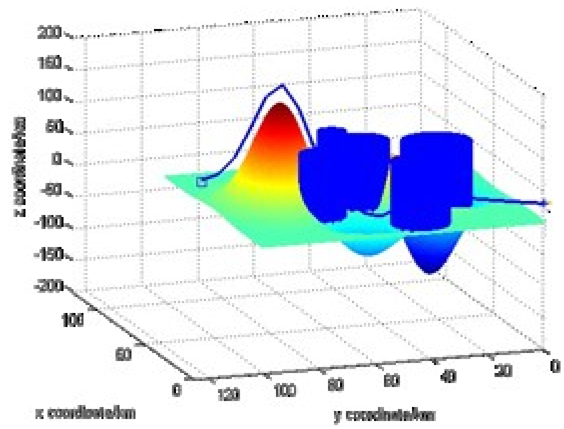

Fig.5 The 3D trajectory planning result of the algorithm

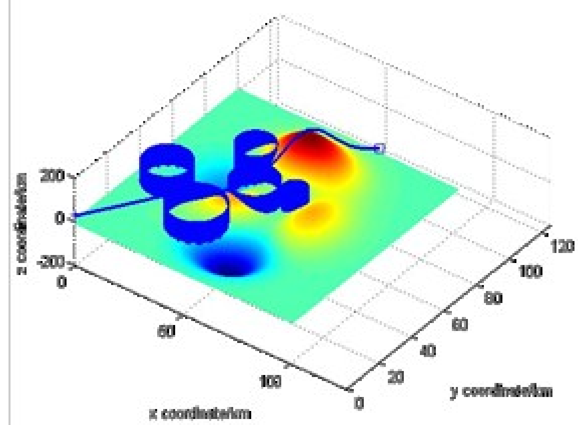

Fig.6 The 3D trajectory planning result of the algorithm

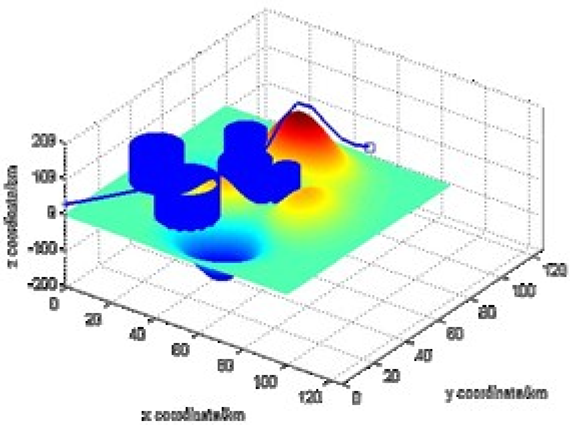

Fig.7 The 3D trajectory planning result of the algorithm

VII. CONCLUSION

This paper presents a novel chaotic DE approach for UAV trajectory planning problem in 3D environment. Utilizing the ergodicity and irregularity of the chaotic variable to help the basic DE algorithm to jump out of the local optimum as well as speeding up the process of finding the optimal parameters. The simulation experiments show that our proposed method is a feasible and effective way in UAV trajectory planning. The experimental comparison also shows the stability and superiority of our method over the standard DE algorithm, which provides a more effective way for UAV trajectory planning.

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