Chaotic Biogeography-Based Optimization Approach to Receding Horizon Control for Multiple UAVs Formation Flight

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Abstract: In this paper, we proposed a Receding Horizon Control (RHC) scheme which converts multiple Unmanned Aerial Vehicle (UAVs) formation flight problem to a sequence of online optimization problems over a planning horizon. A novel Chaotic Biogeography-Based Optimization (CBBO) approach is presented to find the optimal control inputs for the follower UAVs to maintain coordinated flight with the minimum input cost in each of the planning horizons. Series of simulation results verified the feasibility and effectiveness of our presented approach.

Keywords: Unmanned Aerial Vehicles (UAVs); Formation Flight; Biogeography-Based Optimization (BBO)

1. INTRODUCTION

Formation flight of multiple unmanned aerial vehicles (UAVs) is a growing topic of research within the aerospace community, and has a number of applications in military missions such as reconnaissance and surveillance, task allocation and target data acquisition, radio jamming, and the suppressions of enemy air defence as well as in civilian missions such as crop monitoring, area search and rescue (Sujit and Ghose, 2004; Duan et al., 2010). The multiple UAVs formation flight problem aims to achieve desired geometries by controlling the overall behaviour of the group. Accurate maintenance of the formation can often accomplish objectives impossible for a single UAV and lead to certain advantages such as a reduction in the formation's induced drag (Giulietti et al., 2005) and energy saving from vortex force created by the lead aircraft (Pacheter et al., 2001). Development of formation control problems and numerous approaches for UAVs formation control design have been well demonstrated over the past year. R. Sattigeri et al. proposed a decentralized adaptive output feedback approach which allowed the vehicles to maintain the formation while considering obstacles (Sattigeri et al., 2004). W. Ren et al. developed a leaderless formation control scheme based on consensus algorithms which overcome a single point of failure for the formation (Ren and Chen, 2006). W. Lin proposed a novel open-loop Nash strategy design approach for each UAV to solve the UAV formation problem in a fully distributed way (Lin, 2014). Masayuki Suzuki et al. designed a three-dimensional formation control scheme using the new approach of bifurcating artificial potential fields (Suzuki, 2009). Yu Gu et al. conducted multiple UAVs formation flight test. The inner-loop controller is designed to track those desired angles using the classical linear control method, whereas the outer loop guidance law minimizes the position tracking error, using the nonlinear dynamic inversion approach (Gu et al., 2006). But these methods may not be able to deal with the constraints easily (Zhou et al., 2011). Optimization-based approaches can solve the constraints of

UAV formation control systems appropriately and have been proved to a successful way to the multiple UAVs formation problems. Among the most popular optimization-based methods is receding horizon control method.

Receding horizon control (RHC), also referred to model predictive control (MPC), is a feedback control technique which has made a significant impact on industrial process control (Rawlings, 2000), and is being increasingly applied in automotive applications (Chen and Hu, 2007) and aerospace applications (Duan et al., 2011; Richards and How, 2004). In RHC, the designer specifies the objective and constraints as part of an optimization problem, which must be solved at each time step. RHC is a natural technique for formation flight problems of UAVs because they can systematically handle constraints and obtain satisfactory performance. RHC method has been applied to the multiple vehicles formation problems in recent years (Shin and Kim, 2009; Duan and Liu, 2010). However, RHC with conventional numerical optimization techniques costs large computational burden of online optimization and does not always get a satisfactory solution, which limits the performance of RHC approach (Mattingley et al. 2011). Biogeography-Based Optimization (BBO) algorithm is presented in this paper to solve the optimization problem in each time horizon because of its good performance of global exploration and rapid convergence. BBO algorithm is a new evolutionary optimization algorithm based on the science of biogeography for global optimization (Simon, 2008). BBO works based on two mechanisms: migration and mutation. BBO has some features in common with other population-based optimization algorithms like particle swarm optimization (PSO) and genetic algorithm (GA), such as the ability to share information between candidate solutions. However, BBO has certain features which overcome several demerits of the conventional methods. One of the characteristics of BBO is that it maintains solutions from one iteration to the next and improved the solutions by migration (Simon et al., 2011). Furthermore, we introduced the chaos theory to improve the robustness of basic BBO algorithm considering its

outstanding performance in jumping out of local best solution, and the comparative simulation results verified that our proposed method manifests better performance than the original BBO algorithm.

In this paper, we design a controller for multiple UAVs formation problem using a CBBO-based RHC approach. The rest of this paper is organized as follows: Section 2 describes the UAV model and the formation structure. Section 3 specifies implementation procedure of our proposed chaotic BBO (CBBO) algorithm. In Section 4, series of comparative simulations are presented to verify the performance of the proposed approach for multiple UAVs formation. Our concluding remarks are contained in the final section.

2. PROBLEM FORMULATION

2.1 Model of UAV Flight Dynamics and Control Systems

The equations of motion describing UAV flight dynamics are given as follows (No et al., 2011):

$$\dot{v}_i = g[(T_i - D_i)/W_i - \sin\gamma_i] \tag{1}$$

$$\dot{\gamma}_i = (g/v_i)(n_i\cos\phi_i - \cos\gamma_i) \tag{2}$$

$$\dot{\chi}_i = (gn_i\sin\phi_i)/(v_i\cos\gamma_i) \tag{3}$$

$$\dot{x}_i = v_i\cos\gamma_i\cos\chi_i \tag{4}$$

$$\dot{y}_i = v_i\cos\gamma_i\sin\chi_i \tag{5}$$

$$\dot{z}_i = v_i\sin\gamma_i \tag{6}$$

where the state vector $X_i = [v_i, \gamma_i, \chi_i, x_i, y_i, z_i]^T \in \mathfrak{R}^6$ denotes the velocity, the flight path angle, the heading angle, and the inertial position (x_i, y_i, z_i) of the ith UAV, and the control inputs vector $U_i = [T_i, n_i, \phi_i]^T$ denotes the engine thrust, load factor, and bank angle, respectively. D_i is the aerodynamic drag, γ_i is the flight path angle, χ_i is the heading angle, and W_i is the weight of ith vehicle.

2.2 Receding Horizon Control

Receding horizon control (RHC), also known as model predictive control (MPC), is a feedback control scheme in which a finite horizon open-loop optimization problem is solved at each sampling instant (Gu and Hu, 2006).

The RHC procedure works as shown in Fig. 1. At time t, we consider a time interval extending p steps into the future, t, t+1, …, t+p. We then carry out the following steps:

1) Replace all the uncertain quantities over the prediction horizon p with their estimates using the information available at time t to predict the future dynamic behaviour of the system.

2) Optimize a predetermined performance objective function subject to the estimated dynamics and constraints. The optimization result is a plan of action for the next p steps.

3) Determine the input over a control horizon m using the plan of action. At the next time step, the process is repeated, with the updated estimates of the current state and future quantities.
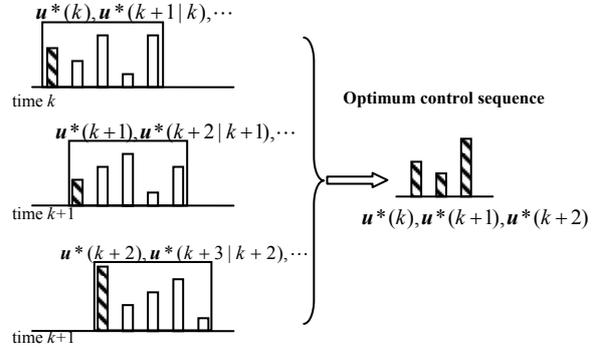

Fig. 1. Procedure of receding horizon control

2.3 Leader-Follower Formation Flight

We formulate a receding horizon control scheme based on the objective function. At time k, the controller predicts a control sequence from time k to time $(k+p)$, which can be represented by $U(k|k)$, $U(k+1|k)$,…, $U(k+p-1|k)$. Using this control sequence and the current state of the system $X(k)$, the state at time $k+1$,…, $k+p$, which are represented by $X(k+1|k)$, $X(k+2|k)$,…, $X(k+p|k)$ can be obtained. The objective function at time k can be defined as:

$$
\begin{aligned}
\min J(k) = &\sum_{j=1}^{p}[X_{ref}(k+j) - X(k+j|k)]^T \cdot Q \cdot [X_{ref}(k+j) - X(k+j|k)] \\
&+ \sum_{j=1}^{p} U(k+j-1|k)^T \cdot R \cdot U(k+j-1|k)
\end{aligned} \tag{7}
$$

subject to

$$\dot{X}(k) = f(X(k), U(k))$$

$$X(k+1) = X(k) + \dot{X}(k) \bullet \Delta t$$

$$U_{\min} \le U(t) \le U_{\max}$$

where Q and R are positive-definite weighted matrices. $X_{ref}(k) = [v_r, \gamma_r, \chi_r, x_r, y_r, z_r]^T$ is reference state of follower UAVs at time k. $X(k+j|k) = [x(k+j|k), y(k+j|k), v(k+j|k), \psi(k+j|k)]$ is the state of follower UAVs at time $k+j$ over the prediction horizon. Δt is the sampling time.

At time k, by minimizing this objective function, an optimal control sequence can be obtained, then only the first m control actions in this sequence is applied to the formation flight system. At time $k+m$, repeat sampling, predicting, optimization and implementing.

2.4 Collision Avoidance Scheme

Collision avoidance is an important aspect in formation flight. By adding a cost function to the optimization problem, we ensure the UAV collision avoidance. We assume that each UAV has a protected zone with radius d_{safe}.

We assume that the ith UAV can obtain the jth UAV's predicted positions in the predicting horizon through communication, i.e. $(x_j(k+s|k), y_j(k+s|k), z_j(k+s|k)), s=1,...,p$. The collision avoidance cost function of the ith UAV is defined as:

$$J_c(X_i,k) = \begin{cases} 0 & , d_{ij} > 2d_{safe} \\ \sum_{s=1}^{p} w_c(2d_{safe} - d_{ij}(k+s|k)) & , d_{ij} \leq 2d_{safe} \end{cases} \quad (8)$$

where w_c is the weighting factor of the collision cost function.

3. CBBO-BASED RHC FORMATION CONTROLLER DESIGN

3.1 Basic BBO Algorithm

Biogeography-based optimization (BBO), suggested by Simon, is a novel population-based optimization technique for solving global optimization problems. It is based on the concept of biogeography, which is the study of the migration, speciation, and extinction of species. In biogeography, a habitat means an ecological area which is inhabited by a particular plant or animal species and is geographically isolated from other habitats. Each of the habitats is considered as an individual with its habitat suitability index (HSI) to measure the goodness for living. A habitat with a high HSI indicates that it is more suited as living places for biological species and tends to have a large number of species while a habitat with a low HSI indicates that it is less suited for species to reside there and tend to have a small number of species. The dynamics of the movement of the species among different habitats is mainly governed by two parameters called immigration rate (λ) and emigration rate (μ) and these two parameters depends upon the number of species in the habitats. From immigration graph of Fig.2, the equation for immigration rate λ_k and emigration rate μ_k for number of species can be written as the following way:

$$\lambda_k = I(1 - \frac{k}{n}) \quad (9)$$

$$\mu_k = E(\frac{k}{n}) \quad (10)$$

where E and I are the maximum emigration rate and maximum immigration rate, and $n = S_{max}$ is the maximum number of species in a habitat.
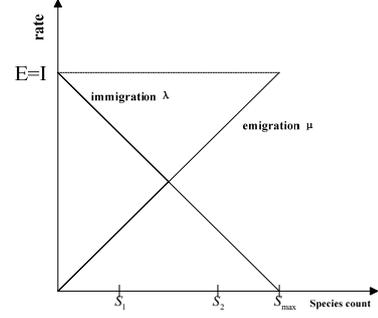

Fig. 2. Species model of a habitat

We assume that each habitat has an identical species curve, with $E = I$ for normalization and simplicity, then combining (9) and (10) gives

$$\lambda_k + \mu_k = E \quad (11)$$

3.2 Chaos Theory

Chaos, apparently disordered behaviour that is nonetheless deterministic, is a universal phenomenon that occurs in many areas of science (Zhu and Duan, 2014). The property of certainty, ergodicity and the stochastic of chaotic sequence have great advantages to enriching the searching behaviour and preventing premature convergence (Caponetto et al. 2003; Xu et al., 2010). In this paper, a chaos variable is introduced as a disturbance through the traditional method in order to optimize the search process.

In this paper, we use the logistic map (May, 1976), its mathematical expression is given as follow:

$$x_{n+1} = f(x_n) = \mu x_n(1-x_n) \quad (12)$$

where $x_n \in [0,1]$ and $x_n \neq 0, 0.25, 0.50, 0.75, 1.0$. μ is called Logistic parameter and is usually set to 4 to obtain ergodicity in (0,1). A tiny difference in the initial value of x would give rise to huge difference in the outcome of the system, which is the basic characteristic of chaos. Even though the chaos system is deterministic, it is not fully predictable. Its randomness ensures the capability conducting a large-scale search and helps to overcome the limitation of local best solutions. Therefore, after each generation of mutation, we conduct the chaotic search in the neighbourhood of the current optimal parameters by listing a certain number of new generated parameters based on the logistic equation. In this way, we 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 simulation results in Section 4 show the efficiency of our proposed method.

3.3 Proposed CBBO Algorithm

Due to the flexibility and robustness in solving optimization problems, BBO algorithm has already aroused intense interest. However, some flaws still exist on this algorithm, such as the large number of iterations to reach the global optimal solution and the tendency to converge to local best

solutions. In order to overcome these flaws of the classical BBO algorithm, CBBO, which integrates BBO with chaos theory, was proposed in our work. After the mutation operation of each generation, conduct the chaotic search in order to choose better solutions into next generation. In this way, our proposed algorithm takes the advantage of the characteristics of the chaotic variable to make the individuals of sub generations distributed ergodically in the defined space and thus to avoid from the premature of the individuals.

To describe the control scheme in detail, the working process of our proposed CBBO-based RHC approach to UAVs formation flight problem during the kth sampling interval (from time k to time $k+m$) is taken for example.

The implementation procedure can be described as follows:

Step 1: Initialize the BBO parameters as well as the RHC scheme parameters, such as the population size p_s and the maximum migration rates E and I (see Fig. 3), the maximum mutation rate m_{max}, and an elitism parameter *Keep*, the prediction horizon p and the control horizon m.

Step 2: According to the multiple UAVs formation model in Section 2, detect follower UAVs states $X(k)$ and the reference states $X_{ref}(k)$, predict the following reference states $X_{ref}(k+1), X_{ref}(k+2),..., X_{ref}(k+p)$. Initialize random habitats of D-dimensional parameters within all the constraints. Each group of parameters represents a possible solution and can generate paths for all of the follower UAVs from time k to $k+p$, and the goal is to find the optimal combination of parameters that can provide relatively satisfactory performance. Initialize the starting iteration NC=1.

Step 3: According to the parameters of the generated habitats, calculate the cost of each solution. The smaller the cost value is, the better performance the solution maintains. Based on the values of HSI, elite habitats are identified.

Step 4: Use immigration and emigration to modify each non-elite habitat probabilistically and recomputed HSI of each modified habitat. Feasibility of a solution is verified when each SIV satisfies equality and inequality constraints of generator as mentioned in the specific problem.

Step 5: Update the species count probability of each habitat. Then, perform mutation operation on the habitats and recomputed each HSI value of new habitats.

Step 6: Conduct the chaotic search to those habitats having a low HSI value after transforming the parameters ranges into (0,1). Among the engendered series of solutions, select the best one and use it to replace a random elite habitat.

Step 7: If $NC < NC_{max}$, go to Step 3. Otherwise, output the optimal control sequence and optimal cost value.

Step 8: Apply the firth m part of the optimal control sequence to update the UAVs states. Go back to step 1 at time $k+m$ and move forward to the $(k+m)$th sampling interval.

4. SIMULATION RESULTS

In this section, we present some simulations illustrating the performance of the proposed CBBO-based RHC scheme for multiple UAVs formation flight. The UAV group consists of one leader and four followers, with the constraints on control input $T \leq 200N$, $-1.5 \leq n \leq 2$, and $-75° \leq \phi \leq 75°$.

The initial conditions of the formation controller are prediction horizon p=3, control horizon m=3, weighting matrices Q=diag(0.01,1,1,10,10,10), R=diag(0.1,1,1). The initial parameters of both classical BBO algorithm and CBBO were adjusted as: population size: $p_s = 20$, maximum immigration rate: I=1, maximum emigration rate: E=1, mutation probability: *PmutationRate*=0.3, elitism parameter: *Keep*=5, and the cycle counter: NCmax=50.

The initial position of the leader UAV is (0, 0, 200)m, and the initial velocity is 50 m/s.While the initial positions of the follower UAVs are set as(-220, 200, 120)m, (-55, -110, 140)m, (-900, -60, 160)m, (-150, -400, 150)m respectively, and the initial velocities of the four UAVs are assumed to be 50 m/s. The initial flight-path angle and heading angle are set to $0°$.

The UAVs are supposed to form a "V" shape formation from the randomly initialized positions. Fig.4 shows the detailed results generated by the control sequences optimized by the proposed method. After the optimal control, the UAVs can move to the desired relative of V-shape formation at the same altitude.
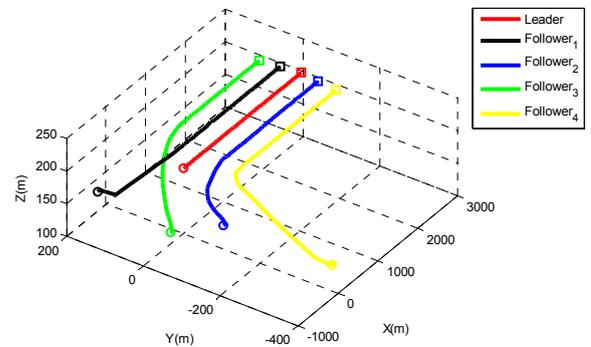
(a) 3-D trajectories of UAVs formation flight
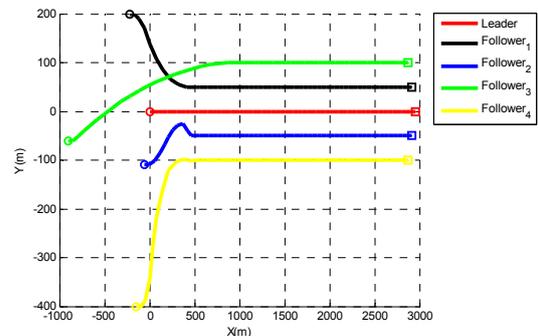
(b) Top view of UAVs formation flight

Fig. 3. Detailed results generated by the control sequences optimized by CBBO algorithm

In our work, in order to show the improvement of exploration ability with the chaos theory, we also described the performances of classical BBO and PSO algorithm. The initial parameters of both classical BBO and PSO algorithm in our simulations were adjusted the same.

With the control sequences optimized by our proposed control method for the follower UAVs, the UAVs group manages to reach the desired configuration from random initial states, whereas the control inputs optimized by BBO and PSO algorithms have inferior performance. Table.1 shows the optimization result of the last iteration.

Table 1. Comparative results of three algorithms

Algorithms	Optimization results
CBBO	474603.50
BBO	667173.42
PSO	17536673.50

This simulation illustrates the effectiveness of our proposed CBBO method compared to the original BBO and PSO algorithm. Control sequences optimized by the CBBO can make the UAVs group merge to the desired formation geometry as shown in Fig.3, compared with the results generated by the original BBO method, CBBO performs better for its ability to global search and high precision.
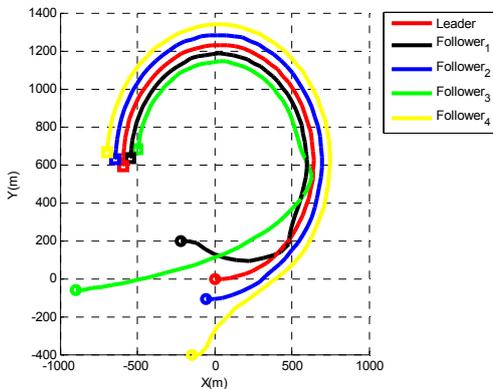

Fig. 4. Trajectories of five UAVs maintain V-formation

Fig. 4 shows the trajectories of five UAVs maintain the configuration while manoeuvring. It is obvious that the vehicle collision avoidance can be guaranteed.

5. CONCLUSIONS

In this paper, we proposed a CBBO-based RHC method for multiple UAVs formation flight problem. The entire formation was composed of one leader UAV and four follower UAVs. The follower UAVs got an optimal control sequence at each time step by the proposed CBBO algorithm which integrated the chaos theory into the original BBO algorithm and successfully generated satisfactory optimization result, while the classical BBO and PSO algorithm may converges to local best solutions due to the large search space. Comparative results were given to show the effectiveness of the proposed control scheme for formation flight.

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