The Optimization of Lateral Control Augmentation based on Genetic Algorithms

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Abstract

The control augmentation systems are very important to keep the stability and manipulability in the flight control systems. The general flight control laws are designed by static designs and dynamic fits. To improve the adaptive capability, a new method of control laws design was introduced by using dynamic optimization genetic algorithms. The control parameters were adjusted online in the flight envelope. The dynamic optimization model was built for aircraft lateral control augmentation function. The control parameters were regulated by dynamic optimization genetic algorithms optimization genetic algorithms optimization genetic algorithms optimization function. The control parameters were regulated by dynamic optimization genetic algorithms. Finally an example of a lateral flight control augmentation system of an aircraft is used with a simulation. The simulation results show the proposed method is achievement.

Keywords: control augmentation, dynamic optimization, genetic algorithms, flight control system

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1. Introduction

In the flight control systems, it is the key technology of controller parameters optimization, which was designed by classical root locus or frequency method. But in this method, we must design lots of controller parameters in order to keep dynamic characteristic of aircraft. With the progress of the optimization technology, there are large numbers of researches for controller parameters optimization based on genetic algorithms [1-4]. Marco Farina introduced a type of controller design method by using dynamic multi-objective optimization [1]. P. J. Fleming analyzed a design method of control systems based on evolution algorithms [2]. Xiangjun Meng studies dynamic optimization for controller [3]. Fangzhen Song used the dynamic optimization to adjust the PID controller parameters [4]. In addition, Literature [5] studied minimum time control of helicopter UAVs by using computational dynamic optimization. Literature [6] studied a intnllience control method. Literature [7-9] researched a flight control laws design for flight control laws, but the flight control systems is time variation systems with flight condition. So it is very urge for dynamic control systems optimization design.

In general, flight control laws are designed by adjusting parameters in equilibrium point, and then controller gains were scheduling in the large flight envelope. It is very important to adjust controller online based on flight state for improvement adaptive capability and complexity of design. In the control and information fields, there are some complex dynamic optimizations problems, which the fitness and objective functions are changed with the time. So in such cases the optimization algorithm has to track a moving optimum as closely as possible, rather than just find a single good solution. The evolution algorithms are difficult to fit environment change when they are convergence. It has been argued that evolutionary algorithms (EAs) may be a particularly suitable candidate for this type of problems. However EAs need to be adapted for optimal results on dynamic optimization problems. When the changes occur, the solution given by the optimization procedure may be no longer effective and may actually be misguiding the search. Over the last decades, researchers have developed many approaches into GAs to address this problem [10-11].

So in the flight control systems, if we can adjust controller parameters with flight condition change by using dynamic optimizations method, we will synchronously deal with the problem of adjusting and scheduling parameters about control laws design. Based on above analyses, we explore a method of dynamic optimization genetic algorithms for flight control laws design in order to deal with controller parameter and gain scheduling together. A lateral flight control augmentation system of an aircraft is used with a simulation. The simulation results show validity of the proposed algorithms.

2. Problem Statement

Generally, a linear model of the lateral dynamic equations of the aircraft is constructed as the follows.

$$\begin{cases} \Delta \dot{\beta} + Y_{\beta} \Delta \beta + \Delta r + Y_{\phi} \Delta \phi = -Y_{\delta_{r}} \Delta \delta_{r} \\ L_{\beta} \Delta \beta + \Delta \dot{p} + L_{p} \Delta p + \Delta \dot{r} + L_{r} \Delta r = -L_{\delta_{a}} \Delta \delta_{a} - L_{\delta_{r}} \Delta \delta_{r} \\ N_{\beta} \Delta \beta + \Delta \dot{p} + N_{p} \Delta p + \Delta \dot{r} + N_{r} \Delta r = -N_{\delta_{a}} \Delta \delta_{a} - N_{\delta_{r}} \Delta \delta_{r} \\ -p + \Delta \dot{\phi} = 0 \end{cases}$$
(1)

Here *p* is body-axis roll rates, *r* is body-axis yaw rates. Y_{\bullet} , L_{\bullet} and N_{\bullet} are body-axis nondimensional aerodynamic parameter. ϕ is roll angle, β is sideslip angle, δ_a is aileron, δ_r is rudder.

The dynamic matrix of the aircraft lateral model is getting through the formulation 1.

$$\begin{bmatrix} \Delta \dot{\beta} \\ \Delta \dot{p} \\ \Delta \dot{r} \\ \phi \end{bmatrix} = \begin{bmatrix} -Y_{\beta} & 0 & -1 & -Y_{\phi} \\ N_{\beta} - L_{\beta} & N_{p} - L_{p} & N_{r} - L_{r} & 0 \\ L_{\beta} - N_{\beta} & L_{p} - N_{p} & L_{r} - N_{r} & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta \beta \\ \Delta p \\ \Delta r \\ \Delta \phi \end{bmatrix} + \begin{bmatrix} 0 & -Y_{\delta_{r}} \\ N_{\delta_{a}} - L_{\delta_{a}} & N_{\delta_{r}} - L_{\delta_{r}} \\ L_{\delta_{a}} - N_{\delta_{a}} & L_{\delta_{r}} - N_{\delta_{r}} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_{a} \\ \delta_{r} \end{bmatrix}$$
(2)

Here, Y_{\bullet} , L_{\bullet} and N_{\bullet} are variable which is changed with velocity and altitude in flight. That is to say the control object is changed with the time. So the design control laws are the dynamic optimizations problems.

In this paper, the flight control laws configuration is tracking the roll rates order, the controller is used by proportion control which the control parameters are k(t). Thus the control laws of the aircraft lateral control augmentation system are as follows.

$$\begin{cases} \Delta \delta_a = k_1(t)p\\ \Delta \delta_r = k_2(t)r - k_3(t)\beta \end{cases}$$
(3)

And then this control problem can become a dynamic single optimizations problem as follows.

$$\min_{\substack{(k_1(t),k_2(t),k_3(t))\in(0.1,5.0)\times(0.1,5.0)\times(0.1,5.0)}} e(k_1(t),k_2(t),k_3(t)) \tag{4}$$

Here $e(k_1(t), k_2(t), k_3(t))$ are errors between roll rates and reference model. The optimization control systems models are as follows. It can be shown in Figure 1.

In this control Schema, the reference model is set up by using lateral flying qualities criteria in order to satisfy the demand of aircraft lateral dutch roll mode.

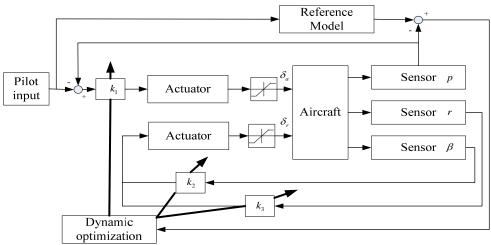


Figure 1. Schema of Dynamic Optimization for a Lateral Control Augmented System

3. Dynamic Optimal Control Laws Design

Dynamic optimal problems are that the fitness, variable and restriction are change with time [12]. For dynamic optimal problems, the design aims are the algorithms must adapt continuingly environment change and track the optimal solution. But the aim of traditional genetic algorithms is population convergence. So it is easy to lose diversity so that lose the adaptive ability for environments. To overcome this defect, the genetic algorithms must keep population diversity so that it can search new field in the dynamic environments.

Based on the above mentioned, an adaptive method is produced in this paper. The search space is divided into near-space and far-space respectively. The new immigrants are randomly generated from both the subspaces. The immigrants from the near-space are used to adapt to the environment changed slightly, and the immigrants from the far-space are used to adapt to the environment changed largely. Considered the characteristic of flight control systems, the search space inspects the environment's changes (velocity and altitude). The change range of the velocity and altitude is divided into near-space threshold $\eta_1(h, v)$ and far-space threshold $n_1(h, v)$ respectively. Thus the algorithms are as follows

space threshold $\eta_2(h,v)$ respectively. Thus the algorithms are as follows.

If the environment changes at the end of generation t corresponding to the k-th change, the optimal solution of the current population is denoted by $x^*(t)$ ($x^*(t)$ is the optimal solution of generation t, let $v(t-1) = x^*(t) - x^*(t-1)$. It is applied with the following formula to generate new individual x_{new} .

$$x^{i}(t+1) = x^{i}(t) + \lambda_{1}v(t-1)$$
(5)

Where λ_1 is random number from [0, 1], which denotes near-space search in near optimal solution. In the far-space, there is algorithm as follows.

$$x^{i}(t+1) = x^{i}(t) + \lambda_{2}v(t-1)$$
(6)

Here, λ_2 is parameter, which denotes the step along the direction. If the parameter is chose exactly, the algorithms can search quickly the optimal solution with the environment change.

Based on the consideration above, for dynamic optimal problem, an adaptive method is introduced to resolve the controller in this paper. The following is the proposed algorithm:

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Step1. $t \leftarrow 0$, initialize population P(t) of scale N in search space [L,V], give the crossover probability p_c , mutation probability p_m , t is generation.

Step2. From P(t), select individuals to form a population P'(t) for reproduction

Step3. Crossover $(P'(t), p_c)$, $(p_c$ is the crossover probability)

Step4. Mutate $(P'(t), p_m)$, (p_m is the mutation probability)

Step5. Evaluate the interim population P'(t)

Step6. Inspect environments, calculate $\mathcal{E}(h, v)$, judge the threshold $\eta_1(h, v)$ and

 $\eta_2(h, v)$, if changes, go to step 7, otherwise, turn step 8;

Step7. Apply adaptive method to adjust the individual from P(t) to form new P(t+1).

Step8. If the termination is not satisfied, $t \leftarrow t+1$, go to step 2, otherwise, stop.

According to above algorithms, the parameters of flight control laws are get, and then those solution are introduced online aircraft controller in order to achieve control results.

4. Simulation Analysis

In order to validate the proposed algorithms, the simulation is presented by using an aircraft model. In this paper, the flight condition is a straight level flight condition at 0~3000 meter altitude and 0.1~0.6 mach. The sampling period is chosen to be 0.01 second, and simulation time is 30 second. An aircraft equilibrium conditions are $\alpha = 3.2301 \text{ deg}$ and

 $\delta_e = -2.23 \deg$. The input signal is aileron δ_a .

A lateral control augmented stability systems are used to simulate analysis, and the simulation results are as figure 2-4. In the simulation the velocity suppose no change and the altitude is changed so that the dynamic environments can be validated. The initial value of the algorithms is chose by doing lots of simulations. When the environment is no change(altitude and velocity keep constant), the control systems can quickly converge for a little disturbance signal ($\beta = 5 \deg$) as for Figure 2. When the systems are input signal, the altitude is changed and exceeds the threshold $\eta_1(h, v)$ in the 10 seconds, and the dynamic optimal algorithms are sprung for Figure 3. The control output achieves the tracking input signal. In the next 10 seconds, the altitude is again changed and exceeds the threshold $\eta_2(h, v)$, the simulation results are as Figure 4. The control output achieves yet the tracking input signal.

According to these figures, it can be seen that, the proposed algorithms are converged quickly. Different environment change has good result. The controller can track quickly the reference orders when the environment changes.

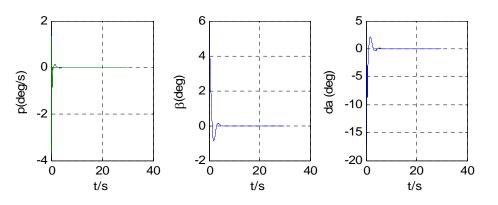


Figure 2. Output Curve in No Environment Change

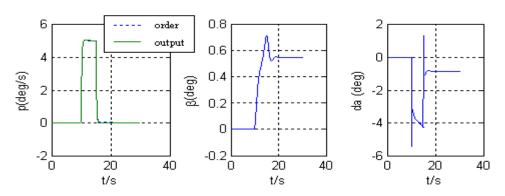


Figure 3. Output Curve in Near-space Change

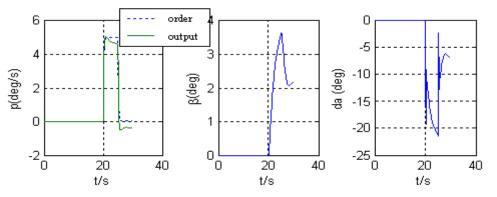


Figure 4. Output Curve in Far-space Change

5. Conclusion

In general, flight control laws are designed by adjusting parameters in equilibrium point, and then controller gains were scheduling in the large flight envelope. We explore a method of dynamic optimization genetic algorithms for flight control laws design. The parameter change of flight control systems is transformed dynamic optimal problems, which is resolved by using dynamic optimal genetic algorithms. A lateral control augmented stability system of an aircraft is used with a simulation. The control laws parameters are adjusted online according flight environment changes. In this paper, we make an attempt to design flight control laws by using dynamic optimization conception, which the condition is ideal. We only take a thought to optimization design of control systems.

Acknowledgment

This work is supported by the National Natural Science foundation of China (No.61105065). This work is supported by "the Foundamental Research Funds for the Central Universities". This work is supported by the Aeronautical Science Foundation of China (No. 20100753009).

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