THE USE OF GENETIC ALGORITHM IN FLIGHT CONTROL SYSTEM DESIGN

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ABSTRACT

A controller for an aircraft called BRAVO is designed by using genetic algorithm. Because the aircraft model is nonlinear and it is important to consider every necessary point in the flight envelope for the design of a flight control system, the multi-model approach has been used. The results presented in this paper showed that the genetic algorithm and multi-model control approach match well for flight control system design.

1. INTRODUCTION

When the motion of any type of vehicle is being studied it is possible to generalize so that the vehicle can be regarded as being fully characterized by its velocity vector. The time integral of that vector is the path of the vehicle through space. The velocity vector, which may be denoted as $\mathbf{x}$, is affected by the position, $\mathbf{x}$, of the vehicle in space by whatever kind of control, $\mathbf{u}$, can be used, by any disturbance, ξ and by time, $\mathbf{t}$. Thus, the motion of the vehicle can be represented in the most general way by the vector differential equation:

$$\mathbf{x} = \mathbf{f}(\mathbf{x}, \mathbf{u}, \xi, \mathbf{t})$$

where $\mathbf{f}$ is a vector function. The means by which the path of any vehicle can be controlled vary widely, depending chiefly on the physical constraints which obtain. Aircraft control problems are usually more complicated than those of other vehicles. Because the aircraft have six degrees of freedom: three associated with angular motion about the aircraft's center of gravity and three associated with the translation of the centre of gravity. [1]

The stability problem of the aircraft may be summarized as computing suitable feedback coefficients from motion sensors to the deflectional surfaces of the aircraft such that flight condition is preserved under external disturbances .

For the straight-symmetric wings-level flight condition it is customary to decouple aircraft dynamics into longitudinal and lateral parts. Using this decoupling order of the differential equations characterizing the aircraft dynamics reduces. This gives rise to obtaining the suitable feedback coefficients with less computation. However, the problem is still complicated and requires along sequence of trial and errors in the computation process. Also requiring that the computed feedback coefficients work satisfactorily within everywhere in the flight envelope increases the computational burden further.[2]

The first step in solving the stability problem is modeling. The model of a conventional aircraft characterizing its motion dynamics is a set of nonlinear differential equations. The second step is linearization of those equations to obtain a set of linear differential equations with constant coefficients. This linearized set represents the motion dynamics about the operating point of interest. Considering the straight- symmetric wings-level flights within a given flight envelope there are infinitely many operating points, since the flight envelope consists of infinitely many altitude-velocity pairs. In practice, designers sample altitude-velocity pairs at sufficiently many points (generally four points for aircraft examples) in the flight envelope.[2]

One of the methods to compute a set of feedback coefficient ranges stabilizing the aircraft is called gain scheduling. In this method the flight envelope is divided into sub envelopes such that it is possible to find a good feedback coefficients set for each sub envelope. Aircraft is programmed to use corresponding feedback coefficients whenever it enters any sub envelope. The other method that we consider, for given altitude-velocity pair designer may select any set of feedback coefficients from computed range. However, designers prefer to select a set of feedback coefficients such that selected set is also a member of the ranges computed for other altitude-velocity pairs of the flight envelope.[2]

Clearly this set of coefficients works for all the sampled points in the flight envelope. Since coefficients of the nonlinear differential equations, and consequently that of the linearized differential equations, are continuous functions of both altitude and velocity, it is concluded that the coefficients work good for any altitude-velocity pairs in the flight envelope. This method is called multi-model approach.

Considering aircraft control problem together with multi-model control approach gave rise us to use genetic algorithm in aircraft control system design.

The genetic algorithms (GAs) can be viewed as general-purpose optimization method and have been successfully applied to search, optimization and machine learning task.

2. MULTI-MODEL CONTROL

The problem of control system design is stated with explicit uncertainty bounds for physical parameters in the plant model and performance bounds as design objectives. A finite number of typical plant parameter values is used to define a multi-model problem[3]. The plant dynamics is not uniquely given, but it is described using multiple candidates of dynamical systems or multiple models.

The technique of multi-model control has two main phases: the location phase and the control phase. Location is an operation by which a comparison is made between the different models to classify them from the system's representation point of view. The best position of each model with respect to the process observations must be determined. The designer must decide on a criterion to evaluate the quality of the models so that they can be classified accordingly.[4]

The control phase of the multi-model technique involves the following two step:

i-) generation of the basic control signal for each model separately by optimization of a vectorial performance index,

ii-) synthesizing the final control signal applied to the process.[4]

Most plant models used for controller design are uncertain. Even if an exact model is available, it may be so complicated that it must be approximated by a simpler, but uncertain, design model. For example, nonlinear models may be linearized for small deviations from an operating condition. Then linear model depends on this uncertain operating condition. Also physical parameters of the plant and its environment may be uncertain. Suppose that the linearized plant is described by a state space model,[3]

$$\begin{aligned} \mathbf{x} &= \mathbf{A}(\Theta)\mathbf{x} + \mathbf{B}(\Theta)\mathbf{u} \\ \mathbf{y} &= \mathbf{C}\mathbf{x} \end{aligned} \qquad (1)$$

where Θ is the vector of uncertain plant parameters. Assume the state variables in $\mathbf{x}$ are chosen such that the output matrix $\mathbf{C}$ does not depend on Θ.

A typical basic problem is that of stability. The coefficients of the closed loop characteristic polynomial are functions of both the plant parameters Θ and the controller parameters $\mathbf{k}$.[3]

$$P(s, \Theta, \mathbf{k}) = p_0(\Theta, \mathbf{k}) + p_1(\Theta, \mathbf{k})s + \ldots + p_{n-1}(\Theta, \mathbf{k})s^{n-1} + s^n$$
(2)

A typical robustness problem is then :Find a $\mathbf{k}$ such that the roots of P(s, $\Theta, \mathbf{k}$) have negative real parts for all $\Theta \in \Omega$. Where Ω is the possible flight conditions in the flight envelope. Or more generally, the set of all such $\mathbf{k}$ if any exist can be find. This problem can be visualized in the combined space Θ and $\mathbf{k}$. In this space a stability region can be determined which contains all ($\Theta, \mathbf{k}$). There are two possibilities to break down the problem into two lower dimensional ones:[3]

i-) For fixed $\mathbf{k}$ we obtain a cross section of the stability region in a subspace with Θ coordinates. If the stability region in this cross section contains Ω, then $\mathbf{k}$ is a solution of the robustness problem. The search for such a $\mathbf{k}$ may be performed in discrete steps in $\mathbf{k}$.

ii-) Similarly the stability region may also be cut a subspace for constant Θ. The set of all stabilizing $\underline{k}$ for this particular value of Θ is obtained. In the aircraft example the latter is the only possible approach because only a finite set of models for $\Theta_1, \Theta_2, \ldots, \Theta_N$ are available. In this case the set of all stability regions in the subspaces for $\Theta = \Theta_1$, $\Theta = \Theta_2, \ldots, \Theta = \Theta_N$ projected into one $\mathbf{K}$-space. This is the multi model approach.[3]

After the set of all stabilizing $\mathbf{k}$ of all stability regions in the subspaces $\Theta_1, \Theta_2, \ldots, \Theta_N$ was determined, the second approach is vectorial performance criteria[3].

Design is a tradeoff between various competing objectives. Some typical design objectives have been formulated in terms of an eigenvalue region. Other objectives are related to feedback gains and their margins; they have been used in the selection of a particular solution from the admissible set.[3]

For each model of the multi model problem ($\mathbf{A}_j, \mathbf{B}_j$), j=1,2,...,N, a performance index must be formed. All these indices may be combined into a vector.[3]

$$\mathbf{g}(\mathbf{k}) = \begin{bmatrix} g_1(\mathbf{k}) \\ g_2(\mathbf{k}) \\ \cdot \\ \cdot \\ g_m(\mathbf{k}) \end{bmatrix} \qquad (3)$$

The optimal value of $\mathbf{g}$ can be find using the different optimization methods (for extending information reader may refer to [5]).

2.1 Application of Multi-Model Approach to Longitudinal Flight Control

The concept of multi-model has long been used In flight control system design. Changes of parameters, such as dynamic pressure, Mach number, weight and balance, and configuration, have a significant influence on the dynamic properties of aircraft, and consideration of every necessary point in the flight envelope is important for the design of a flight control system. Although such design attempts have often been carried out in a trial and error manner based on empirical knowledge, an extension of control theory with the multi-model approach has been proposed for more efficient design.[6]

As it has already been stated, the mathematical model of an aircraft is nonlinear. It may be linearized for small deviation from stationary flight with constant altitude h and velocity v in the flight envelope as shown Eqn. (2). The linearized model depends on the plant parameter vector.

$$\Theta = \begin{bmatrix} v \\ h \end{bmatrix} \tag{4}$$

In this state-space model, the states and parameters for the longitudinal motion of the aircraft are defined as (for extending information reader may refer to [1]),

$$\begin{aligned}
\Theta^T &= [v(m/s) \quad h(m)], \\
\mathbf{x}^T &= [u(m/s) \quad w(m/s) \quad q(m/s) \quad \theta(rad)], \\
\mathbf{u}^T &= [\delta_E], \\
\mathbf{y}^T &= [u(m/s) \quad w(m/s) \quad q(m/s) \quad \theta(rad)],
\end{aligned} \tag{5}$$

$$\mathbf{A} = \begin{bmatrix} X_u & X_w & 0 & -g \\ Z_u & Z_w & U_0 & 0 \\ \tilde{M}_u & \tilde{M}_w & \tilde{M}_q & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

$$\mathbf{B} = \begin{bmatrix} X_{\delta E} \\ Z_{\delta E} \\ \tilde{M}_{\delta E} \\ 0 \end{bmatrix}, \mathbf{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{6}$$

Where U_0 is steady forward speed, g is gravity, and $X_u, X_w, Z_u, Z_w, \tilde{M}_u, \tilde{M}_w, \tilde{M}_q, X_{\delta E}, Z_{\delta E}$, and, $\tilde{M}_{\delta E}$ are called stability derivatives for specified flight condition of the aircraft.

In this paper, we consider pitch orientation control system , for short-period approximation, as shown Fig.1. The performance criteria can be chosen the closed loop damping ratio

$$\mathbf{g(k)} = [\zeta_{sp}(\mathbf{k})] \tag{7}$$

The aircraft dynamics showing in Fig.1 is defined as $\frac{q(s)}{\delta_E(s)}$. In [7], this dynamics for short-period approximation is given by,

$$\frac{(U_0 M_{\delta_E} + Z_{\delta_E} M_{\dot{\alpha}})s + (M_\alpha Z_{\delta_E} - Z_\alpha M_{\delta_E})}{U_0 s^2 - (Z_\alpha + U_0 M_q + U_0 M_{\dot{\alpha}})s + M_q Z_\alpha - U_0 M_\alpha} \tag{8}$$

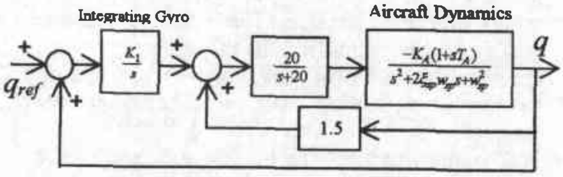

Figure 1. Pitch orientation control

The aircraft dynamics and also the closed loop dynamics at four flight conditions are different from each other. The main control problem is to find a unique controller gain that gives similarly performance criteria value and ensures the closed loop system stability in the longitudinal flight envelope. Because the system stability range and also the performance criteria values in this range changes at the different flight conditions.

The optimal integrating gyro gain must be found according to specified performance criteria. The genetic algorithm can be used to obtain suitable values of K_1.

3. GENETIC ALGORITHM

Genetic Algorithms (GAs) are global numerical optimization methods, patterned after the natural processes of genetic recombination and evolution.

The GA used in this paper known as the simple genetic algorithm. In this algorithm, the three-operator GA with only minor deviations from the original is used.[8]

An initial population of binary strings is created randomly. Each of these strings represents one possible solution to the search problem. Next the solution strings are converted into their decimal equivalents and each candidate solution is tested in this environment. The fitness of each candidate is evaluated through some appropriate measure. The algorithm is driven towards maximizing this fitness measure. Application of the GA to an optimal control problem entails minimizing the selected performance index. After the fitness of the entire population has been determined, it must be determined whether or not the termination criterion has been satisfied. If the criterion is not satisfied then we continue with the three genetic operators : reproduction, crossover and mutation.[8]

Fitness-proportionate reproduction is effected through the simulated spin of a weighted roulette wheel. The roulette wheel is biased with the fitnesses of each of the solution candidates. The wheel is spun N times where N is the number of strings in the population. Copying strings according to their fitness values means that strings with a higher value have a higher probability of contributing one or more off spring in the next generation[9]. This operation yields a new population of strings that reflect the fitnesses of the previous generation's fit candidates. The next operation, crossover, is performed on two strings at a time that are selected from the population at random. Crossover involves choosing a random position in the two strings and swapping the bits that occur after this position. The resulting crossover yields two new strings means the strings are part of the new generation [8]. The crossover rate specifies the number of strings which are effected crossover operator.

The mechanics of reproduction and crossover are suprisingly simple, involving random number generation , string copies , and some partial string exchanges.[9]

The final genetic operator in the algorithm is mutation. Mutation is performed sparingly ,typically every 100-1000 bit transfers from crossover, and it involves selecting a string at random as well as a bit position at random and changing it from 1 to 0 or vice-versa. After mutation, the new generation is completed and the procedure begins again with fitness evaluation of the population [8].

In a control system design using the GA, the parameters that are represented as binary strings are the relevant control parameters.

3.1 GA Design Results

The goal of the genetic algorithm is to determine the value of K_1 which is the integrating gyro gain shown in Fig.1. This value must be ensure closely damping ratio at the four flight point dynamics in the longitudinal flight envelope.

In this paper, we have chosen an aircraft called BRAVO (a twin-engined, jet fighter aircraft) to apply the multi-model approach and also genetic algorithm. The flight conditions parameters and stability derivatives values are given in Table 1 for this aircraft.[1]

Flight Conditions

Parameter	Flight condition 1	2	3	4
Height(m)	S.L.	6100	6100	9150
Mach no.	0.4	0.6	0.6	0.8
$U_0\,(ms^{-1})$	136	190	190	240
$\overline{q}\,(Nm^2)$	11348	11760	11760	10700
α_0 (degrees)	+3.5	+8.5	+8.5	+2.5
γ_0 (degrees)	0	0	0	0

Stability Derivatives
Longitudinal Motion

Stability Derivative	Flight Condition 1	2	3	4
M_α	1.4	-2.7	1.09	0.69
$M_{\dot{\alpha}}$	-0.66	-0.61	-0.54	-0.51
Z_α	-1.02	-0.72	-0.72	-0.54
M_q	-0.53	-0.64	-0.57	-0.48
M_{δ_E}	-11.56	-13.04	-12.25	-12.63
Z_{δ_E}	-0.064	-0.047	-0.047	-0.036

Table 1. Flight conditions parameters and stability derivatives for aircraft BRAVO.

The genetic algorithm program coded in PASCAL, follows the following steps to find suitable value of integrating gyro gain (K_1):

1-) Ask user to enter following parameter values,

. flight condition parameter U_0,

. stability derivatives

$M_\alpha, M_{\dot{\alpha}}, Z_\alpha, M_q, M_{\delta_E}, Z_{\delta_E}$,

. the genetic algorithm parameters; population and generation size, crossover and mutation rate, parameter resolution,

. performance index for closed loop dynamics (ξ_{sp}) and desired standard deviation from this value.

2-) Calculate the aircraft dynamics at four flight conditions using the Eqn.(8).

3-) For each flight condition, find the range of $\mathbf{K}_{1_i}$ $i=1,2,3,4$ which stabilizes the closed loop system. The intersection of the stabilizing $\mathbf{K}_{1_i}$, $i=1,2,3,4$ intervals gives the range of stability for all sampled flight conditions.

4-) Do following steps at each flight condition.

a-) Generate an initial population of $\mathbf{K}_1$ in its range of stability.

b-) The fitness function is defined as normal distribution function,

$$\mathbf{f}(\zeta_{sp}(\mathbf{K}_1)) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(\zeta_{sp}(\mathbf{K}_1)-\mu)^2 / 2\sigma^2}$$

where μ is desired performance index value and σ is specified standard deviation from this value. Using this fitness function and roulette wheel selection , specify new population of $\mathbf{K}_1$.

c-) Apply crossover and mutation operation to selected individuals.

d-) Repeat steps b and c until the specified criteria is met.

e-) Memorize the best fit $\mathbf{K}_1$ interval.

5-) Find intersection of memorized $\mathbf{K}_1$ intervals. If there exist, this intersection ensures closely performance index value at the four flight conditions and also all of the longitudinal flight envelope.

6-) If it is not possible to find any intersection in step 5 ask new standard deviation for the fitness function and go to step 4.

In this algorithm, the genetic algorithm parameters are selected for training cycle as:

Population size	70
Generation size	70
Crossover rate	0.85
Mutation rate	0.05
Resolution of parameter	0.01

The optimum integrating gyro gain was found as

$$K_1 = 8.964$$

when the performance index and standard deviation from this value are selected as 0.4 and 0.1 respectively. For this value of gain, the unit step responses of the system given in Fig.1 is shown in Fig.2.

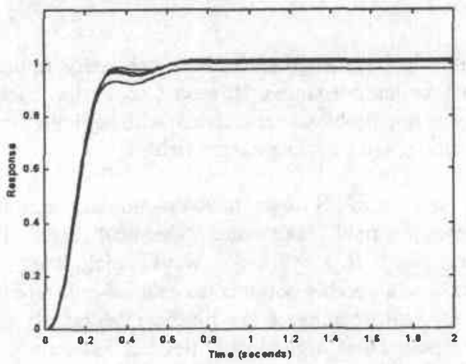

Figure 2. Unit step responses at four flight conditions.

4. CONCLUSIONS

In this paper, a control system design methodology for the longitudinal flight control system was presented. A brief summary of the multi-model control and GA were presented and these two method's application to flight control system design was discussed. The multi-model control gives a good result in point of system stability and system performance criteria. It was found that the GA is suitable for the multi-model control approach and controller parameters found by GA achieved good considered performance criteria.

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