HIGHLY RELIABLE FLIGHT CONTROL SYSTEM DESIGN FOR AUTONOMOUS FLIGHT VEHICLES

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Keywords: *flight control, optimization, reliability, autonomous flight vehicle*

Abstract

In the near future, autonomous flight vehicles will be required to be as reliable as piloted flight vehicles. The flight control computer software that controls the vehicle instead of a human pilot plays a key role in achieving reliable flight control, but with current flight control design specification methods, it is difficult to realize the full potential of flight control software. This paper discusses an approach for ensuring the reliability of flight control software design, specified using a new form of design requirement, that is, probability of mission achievement. This approach is based on the application of stochastic analysis to flight simulation evaluation and the optimization synthesis of adjustable parameters in the flight control program, and has been motivated and proved by research programs using scale-model experimental vehicles. Examples from these research programs demonstrate its validity and effectiveness.

1 Introduction

The recent advancement of digital automatic flight control (AFC) has been changing the nature of flight experiments, which were in the past mainly conducted by challenging the “right stuff” of test pilots, sometimes at risk to their lives. Japanese flight experiment programs such as ALFLEX (Automatic Landing Flight Experiment), HYFLEX (Hypersonic Flight Experiment), HOPE-X HSFD (High Speed Flight Demonstrator), SST (supersonic transport) research vehicles, and HOPE-X (H-II Orbiting Plane Experimental), and recent US X-series programs, are typical examples of programs which have used unmanned vehicles with sophisticated AFC systems that have taken the place of test pilots. It is expected that flight control technology will evolve to realize performance that further exceeds what human pilots have accomplished in the past.

A key factor behind the evolution of flight control technology has obviously been progress in hardware, such as on-board computers (increasing processing power and memory capacity), digital avionics (increasing capability and integration of functions) and digital data communication (increasing speed and bandwidth). Another important factor has been software; methods and tools for designing flight control computer programs. However, the flexibility and potential of software is so great that it is impossible to optimize the design; software is tending to become increasingly complex and this introduces a problem in that the software design, development and verification require much human resources. In other words, the scale of complexity becomes a bottleneck in the flight control software development process, preventing it from achieving potential greater performance and reliability. Although there are many ways to address this problem, this paper discusses two solutions from the standpoint of control law design. One is analysis, or an evaluation method to validate designs, and the other is synthesis, or flight control law optimization and the development of control structures that are amenable to optimization.

For the evaluation method, we propose a form of design specification for automatic flight control; that the probability of total mission achievement be greater than a given minimum value. While this specification appears trivial, to apply it designers must generally use their knowledge and experience to convert the required probability of mission achievement into conventional control system specifications with some margins, which are somewhat rule-of-thumb, and then apply control theories in order to accomplish the goal of "mission success." We propose that this apparently trivial goal can and should be quantitatively evaluated and optimized. Since step-up verification is difficult in space vehicle development, the concept is most required in that area. In other new areas such as autonomous UAVs, where standardized specifications have not been established, our proposed specification will encourage flight control designers to utilize the onboard computer's capability since it is more versatile and general than conventional specifications.

The most critical aspect of this approach is modeling. Although a model should quantitatively define the stochastic properties of all uncertainties, initial conditions, disturbances and noises, this is not possible in general, at least for atmospheric flight vehicles. Therefore, the approach has not been discussed in the research community until recently. However, powerful computers are now readily accessible and the cost of performing computation has decreased drastically. Consequently, conducting huge numbers of flight simulations in conjunction with Monte Carlo methods has become feasible, and so the estimation of stochastic properties for non-linear systems is no longer an issue today. This has led to changes in the way in which automatic flight control systems are developed. Engineers responsible for flight simulation analysis now request models that include quantitative properties of uncertainty for each subsystem, such as aerodynamics, actuators, and sensors. This has been the case for the past ten years of Japanese reentry space vehicle flight demonstrator development programs. In fact, this paper is a product of these programs, in which the success of the flight experiment, or the probability of the vehicle's mission achievement, was the top priority.

A stochastic approach is necessary due to the large number of uncertain parameters and the non-linear nature of their effects. NAL's flight control systems research group has investigated stochastic methods for AFC analysis and synthesis, which apply Monte Carlo simulation (MCS), in order to support highly reliable flight control design for future vehicle development programs.[1][2] The stochastic approach was fully applied to design evaluation of the HOPE-X HSFD program.[3]-[6]

Once the target mission achievement probability has been specified, the flight control program must be tuned to maximize the probability of mission achievement to meet the specification. This approach was partially employed for the landing performance of the ALFLEX reentry vehicle automatic landing demonstrator, where the probability of mission achievement was estimated and maximized over several design parameters. The ALFLEX result was promising, but optimization was conducted only for selected parameters, and what is the best structure for the flight control remains an issue. An approach based on three concepts, separation by time scale, dynamic inversion and control allocation, has been proposed to solve this problem, and some results from ongoing research into reliable reentry space vehicle will be discussed later in this paper.

Much of the content of this paper has previously been published in the authors' papers listed in the references, but has not been summarized in this form hitherto. The paper overviews the approach and discusses key points for actual applications. Section 2 reviews stochastic evaluation and design with Monte Carlo flight simulation by proposing a new form of design specification. Section 3 discusses a method of identifying those uncertain parameters that influence the probability of mission achievement. Section 4 discusses parameter optimization applied to stochastic evaluation, and section 5 describes a general concept for a control structure which is appropriate for the stochastic parameter optimization.

2 Stochastic evaluation of flight control systems

The specification is one of the most important guidelines in flight control system design, MIL-F-9490D being a typical example that has been widely applied to automatic flight control systems. Such specifications describe requirements and design conditions in forms that are tractable for control system analysis methods. For example, stability margin is a typical item in a specification, in which the controlled system can be described by a linear system of a limited order. With the recent advent of robust control design tools, it is not difficult to satisfy the stability margin requirement by modifying the loop shape with a high order compensator, but the result is not necessarily robust because the simple stability margin specification does not imply such a complicated loop shaping. Thus, some specifications are not necessarily appropriate guidelines for advanced control theories to follow for flight control design.

On the other hand, flight simulation is emerging as an increasingly important method for evaluating automatic flight control system design, and has played as essential role particularly in the development of automatic/autonomous flight control systems. Evaluation by flight simulation makes a new form of specification feasible. The following are key points of the new specification.

1) Evaluation items

The results of flight simulation are rather easy to interpret because they are generated in the form of simulated flight test data. Design requirements are defined in terms of limits of flight parameters such as load factor, dynamic pressure, angle of attack, sideslip angle, and touchdown point, and the simulated time histories of these parameters can be directly checked against the limits to see how well each requirement is satisfied. Needless to say, satisfying all of the requirements is the automatic flight control design goal.

2) Design conditions

Since a flight simulation is a computer calculation, its result is repeatable, or deterministic. The reason an actual vehicle's flight behavior is difficult to predict is due to uncertainty, disturbance, and noise; in other words, stochastic nature. It is possible to define a model which describes various design conditions including uncertainty. It is assumed that all the uncertainties are parameterized and their stochastic characteristics are given. Mass parameters, aerodynamics, actuators, and sensors each have their own uncertain parameters. Since external conditions such as atmospheric conditions also have uncertainty, the atmospheric model must also contain uncertain parameters. Errors in the vehicle's initial condition should also be included in the uncertain parameters.

The stochastic characteristics of disturbances and noises, such as gust, sensor noise, and other continuous random variables, are assumed to be given. The simulation program contains a random noise generator whose seed number is one of the uncertain parameters. Noise power spectrum parameters, such as intensity and cut-off frequency, can be included in the uncertain parameters.

3) Flight simulation

A total flight simulation model is constructed from the dynamic models of its components, such as rigid body motion, actuator dynamics, and sensor dynamics. The flight control laws implemented in the vehicle's flight control computer also form a part of the flight simulation model. The models are described by non-linear ordinary differential equations, and the vehicle's behavior is easily evaluated through time integration. The model contains uncertain parameters and adjustable parameters, such as those of the flight control laws. When all the parameters are defined as inputs to the flight simulation, the performance of the vehicle can be evaluated by examining whether or not it satisfies the design requirements.

Fig. 1 shows the concept of evaluation with flight simulation. The evaluation results are functions of the parameters considered to be uncertain, as expressed in the following equation:

$$y_i = f_i(\boldsymbol{x},\boldsymbol{k}) \qquad (1)$$

where y_i is the evaluation result corresponding to a particular parameter; y_i is 1 when the result of the i-th evaluation item meets the specification (is "good"), otherwise y_i is zero. $\boldsymbol{x}$ is a vector of all uncertain parameters. Since the flight control system affects the result of evaluation, $\boldsymbol{k}$ is a vector of adjustable design parameters embedded in the flight control program. If the flight control system is well designed, it is expected that y_i will be 1 in the vicinity of a nominal point in the uncertain parameters' space. Since the function $f_i(\boldsymbol{x},\boldsymbol{k})$ is non-linear, the result should be calculated for all parameters $(\boldsymbol{x},\boldsymbol{k})$.

If the stochastic properties of the uncertain parameters, or the probability distribution density functions of the uncertain parameters $P(\boldsymbol{x})$, are given, the probability of satisfying the i-th evaluation item is given by the following multiple integration in the uncertain parameters' space, where $\boldsymbol{x} \in R^n$.

$$P_i(\boldsymbol{k}) = \int \cdots \int f_i(\boldsymbol{x},\boldsymbol{k}) P(\boldsymbol{x}) dx_1 \cdots dx_n \qquad (2)$$

The probability of satisfying all the requirements $P_o(\boldsymbol{k})$ is then given by

$$P_o(\boldsymbol{k}) = \int \cdots \int \{\prod f_i(\boldsymbol{x},\boldsymbol{k})\} P(\boldsymbol{x}) dx_1 \cdots dx_n \qquad (3)$$

$P_o(\boldsymbol{k})$ is the variable of major concern in the flight control system design. When the number of uncertain parameters is large, numerical integration of the multiple integrals in (2) and (3) are impossible. The Monte Carlo simulation method, however, can give an approximation.

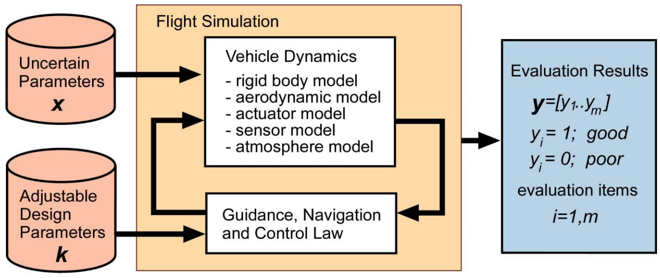

Fig. 1 Evaluation with flight simulation

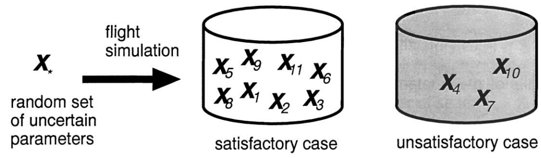

Fig. 2 Probability estimation by Monte Carlo method

4) Probability estimation by the Monte Carlo method

Fig. 2 shows the concept of probability estimation by the Monte Carlo method. Uncertain parameters are randomly generated to satisfy the probability density function $P(\boldsymbol{x})$. For each case, the time histories obtained from a flight simulation can be used to evaluate whether or not the flight control system satisfies the requirements. When it satisfies all the requirements, it can be claimed that the flight control system performs the mission successfully. The Monte Carlo method examines the vehicle's behavior at many discrete points in the n-dimensional space of uncertain parameters. Since the set of generated points is a sample of the probability density function $P(\boldsymbol{x})$, the ratio of numbers of successful cases to total cases becomes an estimate of $P_o(\boldsymbol{k})$.

5) Specification

It is a flight control system design goal that the probability of mission achievement $P_o(\boldsymbol{k})$ is greater than a target value which can be specified. The greater the probability of mission achievement the more reliable the flight control design is considered to be. This goal itself would be trivial were it not for the fact that conventional design specifications do not address it explicitly. Reasons why this proposed specification has not been used hitherto include: 1) it was difficult to quantitatively define the stochastic properties of uncertain parameters, 2) automatic/autonomous flight was not and did not have to be very sophisticated, and 3) Monte Carlo simulation was time consuming. The last reason has been changed with the advent of low cost computers and distributed computing. The second reasons are not applicable to modern flight vehicles such as UAVs. The first reason has been diminishing for each subsystem, such as aerodynamics, structural dynamics, avionics, mechanical systems, due to strong demands for high reliability in flight vehicle development.

Probability distribution function

Definition of the probability distribution function of each uncertain parameter is crucial for this approach. The normal and uniform distributions are the most common forms of distribution function. The normal distribution is defined by mean and standard deviation parameters, and the uniform distribution is defined by upper and lower bounds. In case of the normal distribution, cross correlation is easy to define by using a covariance matrix. In the ALFLEX analysis, a normal distribution was used, and cross correlation was not considered except for one of the aerodynamic uncertain parameters. In the HSFD analysis, a mixture of normal and uniform distributions was used depending on the uncertain parameter.

The values of distribution parameters, such as mean and standard deviation or upper and lower bounds, might not be simple to obtain in practice. In order to obtain a highly reliable flight control system, however, the standard deviation and width of the upper and lower bounds should be great enough to include all possibilities. Unless sufficient information is available, a large error width should be considered. This conservative design analysis often gives an unsatisfactorily low probability of mission achievement in the early stages of actual flight control law design, but the results are useful in achieving a safer design. The results will give information on the crucial parameters for which the uncertainty level should be more precisely defined. A tool for this analysis is discussed in the next section.

Figures 3 and 4 below show analyses for two recent flight experiments, HSFD Phases 1 and 2. The fully autonomous HSFD1 experimental vehicle had an automatic take-off and landing capability, and Fig. 3 shows its simulated and actual landing performance. Touch down position, velocity and sink rate of one thousand Monte Carlo simulation cases are plotted together with the results of three actual flights indicated by symbols. Flight control performance evaluation items such as path error, normal acceleration, angle of attack, sideslip angle, and dynamic pressure were also verified by MCS before the flight experiment. The MCS results proved the reliability of the flight control design, and this was verified by the flight tests.

Fig. 4 is from the terminal guidance performance analysis of HSFD Phase 2. Four thousand MCS results of terminal position are plotted, where the cone indicates the terminal position requirement limits. The vehicle had to reach one of a small number of recovery areas from a quite uncertain initial position because it would be dropped from a high altitude balloon, the position of which was uncontrollable. The MCS results proved that the flight control design had a satisfactory level of reliability for the flight experiment to be conducted.

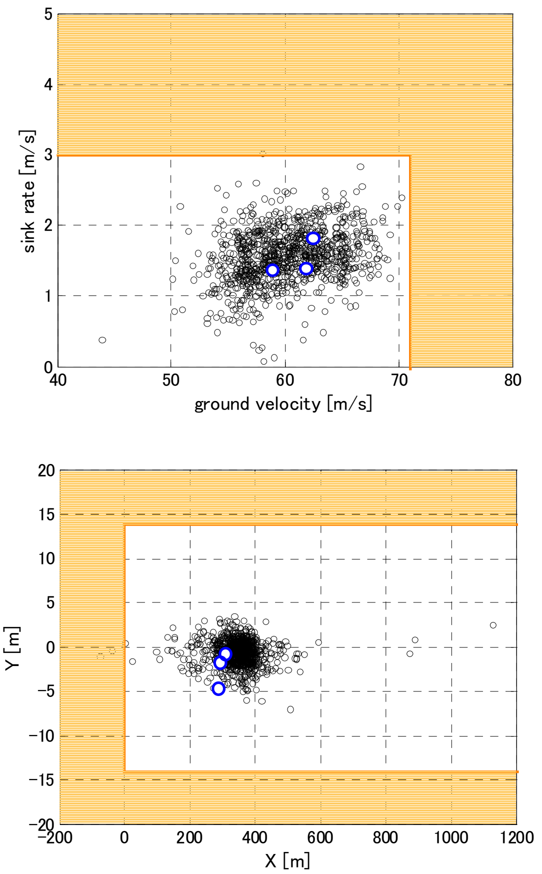

Fig. 3 Landing performance (HSFD Phase 1)

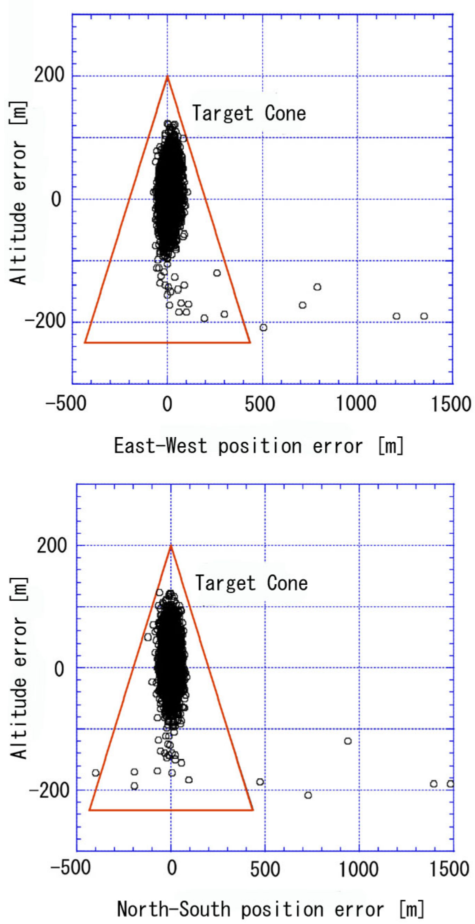

Fig. 4 Terminal guidance (HSFD Phase2)

3 Identification of influential parameters

The probability of mission achievement is a clear design target for flight control system design, and if the estimated P_O failed to meet the target, this would be a problem to be solved. One way of solving this is to refine the probability distribution functions of uncertain parameters, which might incur additional costs. Before reducing parameter uncertainties, it is necessary to identify those parameters which are influential on the probability of mission achievement. Sensitivity analysis for each parameter is a typical approach, but it does not give complete information, especially on the effects of combinations of uncertain parameters. An approach to identify the parameters influential on mission success was developed by applying a statistical hypothesis test. The uncertain parameters can be manipulated to efficiently identify those that are influential, and so the influential parameters can be estimated with a small number of simulation cases.

Fig. 5 shows an example of statistical hypothesis testing for the ALFLEX simulation analysis. The vertical axis indicates a probability which is calculated under the null hypothesis, "each uncertain parameter has no influence on the MCS unsatisfactory result." If the probability becomes less than the level of significance, the null hypothesis is rejected and the corresponding uncertain parameters are decided to be influential. In this example, three parameters are identified as influential on the landing requirement. As shown in Fig. 5, these parameters are likely to be identified as the number of simulation increases. See Ref. [7] for the detail.

Based on this analysis, we can plan to reduce the uncertainty level of specific influential parameters to increase the probability of mission achievement. In practice, reducing uncertainty levels might not be possible, or at least may require additional testing or higher grade equipment. This would be a matter of system design, but a quantitative analysis on the trade-off between uncertainty level and the probability of mission achievement is important.

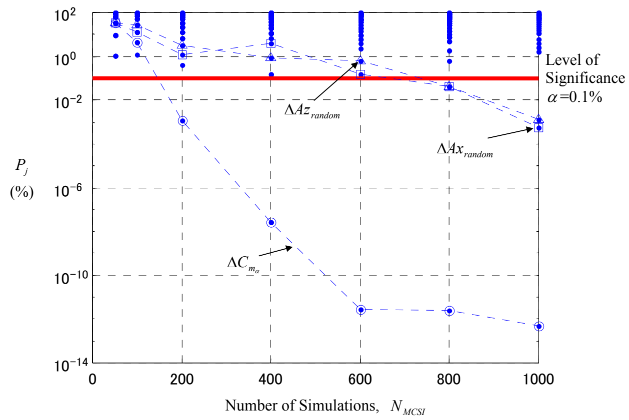

Fig. 5 Influential parameter identification [7]

4 Flight control design with stochastic parameter optimization

The probability of mission achievement P_O is a function of the adjustable parameters $\boldsymbol{k}$ in the flight control law. If the estimated P_O fails to meet the target, it is necessary to redesign the flight control law or to modify the adjustable parameters $\boldsymbol{k}$.

Stochastic parameter optimization (SPO) maximizes P_O. There are, however, a number of difficulties in applying this method, such as: 1) the performance index estimated by MCS contains some error or noise, 2) although the number of adjustable design parameters is not necessarily small, it should be free from the “curse of dimensionality”, and 3) a large number of MCS samples is required because flight control systems are highly reliable.

As a parameter optimization algorithm, the downhill simplex method combined with simulated annealing has been proposed to overcome these difficulties in application to flight control problems. [8][9]

A bottleneck of stochastic approaches such as MCS and SPO is the amount of computation required. However, advances in computer technology have been reducing this bottleneck, and in order to accelerate the solution, NAL has introduced a distributed computer system in which multiple computational nodes share the MCS calculation. It has been verified that the computational performance of this system increases in proportion to the number of nodes.

When the Monte Carlo method uses randomly chosen parameters, the design concept is the same as that of multiple models, although the number of cases is generally much greater in the Monte Carlo method than in the multiple models method.[10] The large number of cases considered by the Monte Carlo method can enhance the reliability of the flight control design.

This approach has already been discussed in part for the landing performance of a reentry space vehicle. The probability of mission achievement was maximized over several design parameters. Fig. 6 is from the ALFLEX post flight analysis. The probability of failing to meet mission requirements was significantly reduced by optimizing seven design parameters in the longitudinal guidance law.

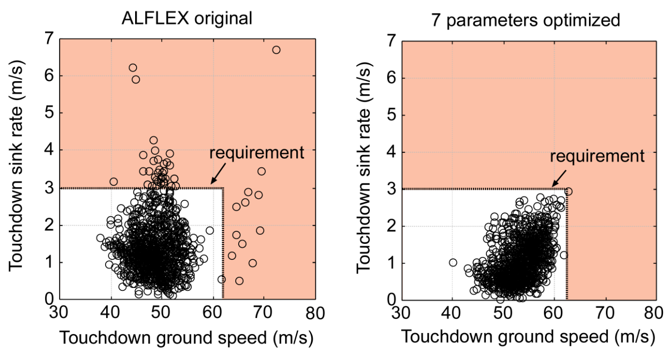

Fig. 6 Example of design parameter optimization (ALFLEX post flight analysis) [8]

5 Control structure

Although the result of the previous section was promising, optimization was conducted only for selected parameters. Since the flight control software program installed in the onboard computer affects the probability of mission achievement, parameters such as feedback gains, limiter values and scheduling parameters can be tuned in order to increase the system reliability. An issue is to select a control structure that is appropriate for optimizing flight control parameters, and conventional multi-variable linear control with dynamic compensators are one possibility. The structure of these conventional controls, however, contains a large amount of adjustable parameters such as feedback/feedforward gains and dynamic compensator coefficients, and it is difficult to identify a limited number of influential parameters. It is therefore necessary to use a control structure that has comparable function with conventional ones but has fewer adjustable design parameters.

We have tried a combination of three concepts to solve this problem; separation by time scale, dynamic inversion and control allocation. These are relatively popular in modern flight control, especially when the flight vehicle has sufficient control capability over rotational motions. Since dynamic inversion and control allocation use data from their own dynamics in real time, they design some of the gains on-line, so the number of adjustable parameters can be limited. Details of these three concepts are as follows.

1) Time scale separation
Dynamic inversion flight control is applied to a divided part of the flight dynamics using a concept of time scale separation. It is assumed that the vehicle's dynamics can be broken down into first order systems. Since first order systems are the simplest, this makes dynamic inversion straightforward. The assumption is possible if a control variable is selected appropriately from among the variables appearing in the time derivative of the controlled variable.

2) Dynamic inversion
Dynamic inversion, sometimes called "feedback linearization", is a typical control structure that uses the vehicle's flight characteristics measured in real time. When dynamic inversion is applied to each dynamics separated by time scale, the flight control program is simplified and the number of adjustable parameters is reduced, especially when gain scheduling is not necessary. In general, variables are categorized in time scale from fast to slow; rotational angular rate, attitude, velocity, and position in that order, where each has three variables corresponding to the vehicle's three axes.

3) Control allocation
Control allocation is a static inversion problem. When a vehicle has redundant multiple control surfaces, control allocation is necessary to distribute a moment command among the control surfaces.

Dynamic inversion has been widely applied [11][12]. Costa has studied the application of dynamic inversion and control allocation to the attitude control of a reentry vehicle [13]. Dynamic inversion does not explicitly consider robustness against uncertainty, but feedback gains or poles assigned for the error dynamics are means to adjust the robustness. Even in dynamic inversion control, it is possible to use scheduled gains to achieve greater robustness than using fixed gains. Tuning is necessary for the feedback gains, and is generally conducted by trial and error. We propose that these gains be determined by the stochastic evaluation; i.e. that the gains are optimized so as to maximize the probability of mission achievement.

The proposed control structure is being applied to a HOPE-X model and a meteorological UAV. Reference [14] application to a HOPE-X model provides a numerical example.

6 Concluding Remarks

This paper overviews an approach for highly reliable flight control system design, in which stochastic analysis, flight simulation and design parameter optimization are key elements. The approach was developed in scaled-model flight experiments for space vehicle technology research, where autonomous experimental vehicles are required to be highly reliable, and successful development of the experimental vehicles' flight control laws has proved its capability. The approach can be applied to automatic flight control system design for any type of vehicle. In particular, the specification proposed in the paper will be effective for highly reliable autonomous UAV. UAVs are heavily dependent on their flight control software, which is extremely flexible and is often difficult to evaluate in terms of specifications established for manned aircraft. It is expected that the specification will make automatic flight control design highly reliable, and that it will promote application of various promising design concepts to actual flight vehicles.

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