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Stochastic Parameter Tuning Applied to Space Vehicle Flight Control Design

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The feasibility of applying the stochastic parameter tuning method to the design of space vehicle flight control systems is studied. Stochastic parameter tuning is a form of optimization by which the probability of the flight control system's total mission achievement is maximized. Mission achievement probability is estimated by applying the Monte Carlo method to the results of a large number of simulated flights. The flight simulation models contain various types of uncertain parameters, the stochastic properties of which are defined a priori. The flight control system requirements are defined based on the results of the flight simulations, and an optimization algorithm called the mean tracking technique is used to tune the feedback/feedforward gains and other adjustable parameters of the flight control laws to maximize the probability of satisfying the requirements. The feasibility of the stochastic parameter tuning method is demonstrated by applying it to the design of the flight control system of a reentry space vehicle, a low-speed subscaled model of which was flight tested in 1996. The stochastic parameter tuning method improves the robustness of the flight control system. Although stochastic parameter tuning requires large computational resources, the recent advent of low-cost, high-performance computers means that it has become feasible and practical. Furthermore, distributed computation can allow a large number of flight simulations to be conducted within limited time and cost constraints. An asynchronous parallel computation using distributed low-cost computers is applied to the Monte Carlo flight simulation.

I. Introduction

ROBUSTNESS against uncertainty is an essential property for flight control systems. The robustness requirements are so explicitly discussed for high-performance flight vehicles because the vehicle's design must maximize flight control performance against uncertainty. A typical example is a reusable space vehicle, where the flight control design is a key factor determining mission feasibility or payload capability.

Robust control is one of the most rapidly advancing fields of control engineering, and there have been extensive efforts to apply its theoretical results to flight control systems. Although some of these efforts have been successfully realized in the design of control systems for real flight vehicles, most merely remain at the level of research and analytical trials, and even at present, it seems difficult to find an established design technique based on robust control theories. Furthermore, robust control evaluation methods have not yet been used for setting flight control system design criteria. One of the reasons for the slow introduction of robust control theory to the design of practical flight vehicles has been the difficulty in expressing real uncertainty encountered in flight control design in forms that can be dealt with by the theories.

In contrast, flight simulation plays a very important role in the design of flight control systems. Such technology is essential for evaluating the control system's performance, and particularly for uninhabited vehicles and automatic flight control systems. This role has continued to expand as computing power has increased. Flight simulation generally includes uncertainty, which can be represented by parametric models, and uncertain parameters exist in a wide variety of simulation components such as aerodynamics, actuator dynamics, sensor dynamics, environmental conditions, and so on. Because the effects of various combinations of uncertain parameters must be considered, it is inevitable that stochastic methods must be applied to evaluate the total system performance, and for this reason, it is necessary to define the probability distribution functions of the uncertain parameters. If these functions are assumed appropriately, it is possible to estimate the stochastic properties of the flight control system by the Monte Carlo method, a technique known as Monte Carlo flight simulation. Because flight simulation clearly determines whether the vehicle satisfies requirements and specifications, Monte Carlo flight simulation can be used to estimate the probability of satisfying the requirements, or the probability of total mission achievement, which is the most critical variable to be maximized in flight control system design. This paper discusses a parameter optimization approach for maximizing the probability of vehicle mission achievement.

The stochastic evaluation and optimization of flight control systems was first studied by Ray and Stengel, who introduced the term stochastic robustness.[1] The basic idea of the approach was proposed by Marrison and Stengel,[2,3] and recently, Schubert and Stengel have proposed using parallel computation for flight control optimization.[4] The original point of this paper is that stochastic optimization is applied to a full-flight simulation, for which the final design goal is explicitly presented. Although application to full-flight simulation inevitably demands large computational resources, the results obtained have indicated that the approach is nonetheless worthwhile. Because this paper's approach is characterized by an optimization algorithm that iteratively improves the probability of mission success over the original design, this stochastic parameter optimization can be called a stochastic parameter tuning method. Furthermore, when most of the tuned parameters are flight control system gains, this approach can be called a stochastic gain tuning method.

This research was motivated by the H-II Orbital Plane Experiment (HOPE-X) Japanese reentry space vehicle development program, which is being conducted by the National Aerospace Laboratory and the National Space Development Agency of Japan to develop and demonstrate technologies for uninhabited reentry space vehicles. Because the HOPE-X vehicle must demonstrate full performance from its first launch flight, its development relies heavily on analysis by flight simulation. Furthermore, HOPE-X requires efficient design tools to optimize flight control performance against uncertainty to afford sufficient payload capability for future missions.

The stochastic parameter tuning method was first studied during the postflight review analysis of the flight control system design of the automatic landing flight experiment (ALFLEX), which was a subscaled model flight experiment for the HOPE-X program.[5] Although the analysis was conducted for the case of two adjustable design parameters, it demonstrated potential for significantly

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improving the automatic landing performance. This paper proposes a development of this optimization technique that is applicable to a large number of adjustable design parameters and further demonstrates the feasibility of the stochastic parameter tuning method with examples from the ALFLEX application.

The paper is organized as follows. Sections II and III describe the basic ideas of the stochastic approach and optimization, focusing on the flight simulation model with uncertain parameters and the Monte Carlo methods. Section IV extends these points to a design problem, where an optimization algorithm suitable for stochastic parameter tuning is presented. In Sec. V, the algorithm is applied to the flight control design of an automatic landing system for a reentry space vehicle. The landing phase is the most demanding on the flight control system across the entire reentry atmospheric flight phase. Section VI describes the computer system used for the stochastic parameter tuning, in which distributed computers connected by a local area network conducted the flight simulation computations in parallel. Finally, Sec. VII presents the conclusions.

II. Flight Simulation with Uncertain Parameters

A flight simulation model is constructed from dynamic models of its components, such as rigid-body motion, actuator dynamics, sensor dynamics, and so forth. The flight control laws implemented in the vehicle's onboard flight control computer also form a part of the flight simulation model. The models are described by nonlinear ordinary differential equations of each state vector.[6] Through time integration of the states, the behavior of the flight vehicle is easily evaluated by the resulting state time histories. The structures of the models are generally based on kinematics, and each model contains parameters that have nominal values but also a degree of uncertainty. When all uncertain and adjustable parameters (such as those of the flight control laws) are defined as inputs to the flight simulation, the performance of the flight vehicle can be evaluated by examining whether or not it satisfies each design requirement. Figure 1 shows the concept of this method of evaluation.

Let $\boldsymbol{x} \in R^n$ be a vector of all uncertain parameters and $\boldsymbol{k} \in R^r$ be a vector of adjustable design parameters. Also, let $\boldsymbol{y} \in R^m$ be a vector of the simulation result outputs. When the ith design requirement is satisfied, for example, runway touchdown position within a certain area, is satisfied, y_i is set to 1, otherwise it is set to 0.

The dependency of $\boldsymbol{y}$ on $\boldsymbol{x}$ and $\boldsymbol{k}$ is represented functionally as

$$\boldsymbol{y} = F(\boldsymbol{x}, \boldsymbol{k}) \tag{1}$$

The flight simulation's calculation itself is very definite, that is, it is repeatable and deterministic. The uncertain nature of the vehicle's performance is due to the uncertainty of the parameters $\boldsymbol{x}$, where uncertain parameters $\boldsymbol{x}$ are used even in the case of seed numbers for continuous noises and disturbances random signal generation. When the probability distribution function of uncertain parameter $\boldsymbol{x}$ is defined as $P(\boldsymbol{x})$, the probability P_i that the vehicle's design satisfies the ith requirement is

$$P_i = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} F_i(\boldsymbol{x}, \boldsymbol{k}) P(\boldsymbol{x})\,\mathrm{d}x_1, \ldots, \mathrm{d}x_n \tag{2}$$

and the probability P_0 that the design satisfies all of the requirements is

$$P_0 = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \left\{ \prod_{i=1}^{m} F_i(\boldsymbol{x}, \boldsymbol{k}) \right\} P(\boldsymbol{x})\,\mathrm{d}x_1, \ldots, \mathrm{d}x_n \tag{3}$$

Probability P_0, which can be called the probability of the system's total mission achievement, directly shows the robustness of the vehicle's flight control system. Estimating the value of P_0 is, therefore, very important to evaluate the flight control system design, and P_0 is a performance index that should be maximized in the flight control law design. Although the probability distribution functions of the uncertain parameters are difficult to define, they can be assumed based on analysis, empirical data, and ground tests. Probabilistic modeling of the uncertain parameters is essential for the stochastic evaluation of the system's performance. Before discussing optimization of adjustable parameters, the calculation of the value of P_0 is reviewed in the following section.

III. Monte Carlo Simulation

When the dimension of vector $\boldsymbol{x}$ is large, the numerical integration of Eqs. (2) and (3) requires an extraordinarily large amount of computation, so much as to be impracticable. The Monte Carlo method is an efficient way of estimating the probabilities P_i and P_0, in which the elements of $\boldsymbol{x}$ are generated randomly in accordance with their given probability distribution functions. Figure 2 shows the concept of Monte Carlo simulation. After $\boldsymbol{x}$ is defined, each y_i can be evaluated from the flight simulation result that uses $\boldsymbol{x}$ as its input. The probability of meeting each design requirement can then be estimated from the statistical properties of a large number of calculated $\boldsymbol{y}$ samples.

The reliability of the estimated probability obtained by the Monte Carlo method can be determined using statistical theory and is dependent on the number of samples. If the system design target is specified as the lower bound on the probability of mission achievement, the estimated P should be higher than a value that is the sum

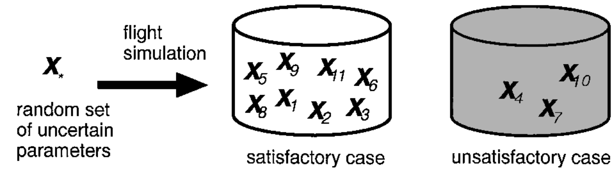

Fig. 2 Monte Carlo simulation concept.

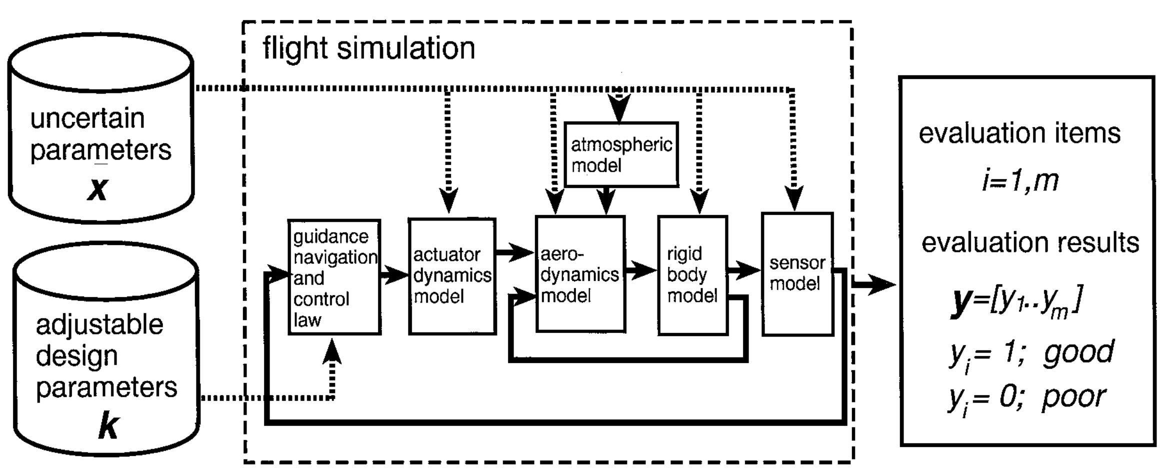

Fig. 1 Uncertain parameters and flight simulation.

of the design target probability and a quantity to account for the estimate's reliability.

The probability of mission achievement is a clear design target for flight control system design, and if the estimated P_0 fails to meet the target, further design effort is necessary. As shown in Fig. 1 and Eq. (1), $\boldsymbol{y}$ is a function of parameters belonging to two categories, namely, uncertain parameters and adjustable design parameters, and so there are two ways of solving such a problem. One is to reconsider the probability distribution functions of uncertain parameters, and the other is to modify the adjustable parameters and will be discussed in detail in later sections.

Changing the probability distributions of uncertain parameters incurs additional costs, such as higher performance hardware, additional ground testing, and so on. To minimize such costs, it is important to study the degree of influence of each uncertain parameter on mission achievement to find the most efficient way of increasing the probability of mission success. Sensitivity analysis and rss analysis are standard methods of predicting these influences.[5,7] The statistical properties of the Monte Carlo simulation cases that do not satisfy the requirements can also show the degree of influence of individual parameters on overall mission performance. If the distribution of values of a certain parameter in such unsatisfactory cases differs from its given probability distribution function, then that parameter can be reckoned to have a high influence on mission achievement probability. Design tools for efficiently reshaping probability distribution functions are useful in the development of reentry space vehicles.

IV. Stochastic Parameter Tuning and the Optimization Algorithm

Stochastic parameter tuning is an optimization in which probability of mission achievement as estimated by Monte Carlo simulation is used as the performance index.[8] Flight control laws contain various parameters that can be adjusted or tuned. After the design parameters $\boldsymbol{k}$ to be adjusted are selected, they can be optimized to maximize the probability of mission achievement because this quantity is a function of the parameters as shown by Eq. (3). However, there are a number of difficulties in applying this stochastic optimization method compared with ordinary parameter optimization problems, and the following three items are the most typical:

1) The performance index value is the result of Monte Carlo simulation and so inevitably contains some error or noise that makes application of simple gradient-based methods difficult.

2) The number of adjustable design parameters is not necessarily small and may be on the order of 10 in a typical flight control system design. The optimization algorithm chosen should be applicable to problems containing parameters of any degree of freedom. In other words, it should be free from the curse of dimensionality.

3) The flight control system is part of a highly reliable system. The allowable probability of mission failure due to unsatisfactory flight control system performance might be less than a few percent even for experimental flight vehicles and would be less than 1% for an uninhabited reusable space vehicle's first flight. This means that a large number of Monte Carlo simulation samples are required, perhaps 1000 or more, which imposes a large computational burden.

The mean-tracking technique is adopted as an optimization algorithm for its reliability and efficiency,[9] and its applicability is basically independent of the number of design parameters. The algorithm consists of iterative shifting of the adjustable design parameters. An initial point in design parameter space is determined, and a small area in the vicinity of this point is searched. Based on the result of the search, the point is then shifted to a location that gives a higher probability of mission achievement.

Figure 3 shows the iteration of shifting the parameter by mean tracking. The basic iterative process is as follows. Let $\boldsymbol{k}_i$ be a vector of adjustable design parameters in the ith iteration. Stochastic properties in the vicinity of $\boldsymbol{k}_i$ are searched to shift the parameters to a point that gives a higher probability of satisfying the design requirement. The search area is defined as

$$\boldsymbol{k}_i - \Delta\boldsymbol{k} < \boldsymbol{k} < \boldsymbol{k}_i + \Delta\boldsymbol{k} \tag{4}$$

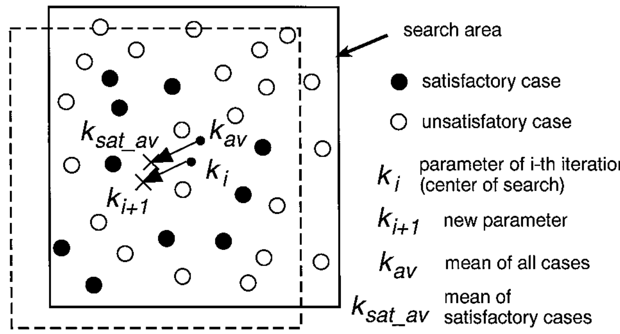

Fig. 3 Parameter shifting by mean-tracking method.

where $\Delta\boldsymbol{k}$ is a parameter to be appropriately defined. N random samples of $\boldsymbol{k}$ are generated, which are uniformly and independently distributed over the rectangular search area. N random values of the uncertain parameters $\boldsymbol{x}$ are also generated according to their given probability distribution functions. Performance evaluation is then conducted for N random combinations of $(\boldsymbol{x}, \boldsymbol{k})$, and the design parameter $\boldsymbol{k}$ is then shifted to the mean of the cases that were satisfactorily evaluated, as follows:

$$\boldsymbol{k}_{i+1} = \boldsymbol{k}_i + \boldsymbol{k}_{\text{sat\_av}} - \boldsymbol{k}_{\text{av}} \tag{5}$$

where $\boldsymbol{k}_{\text{av}}$ is the average of all the samples of $\boldsymbol{k}$, and $\boldsymbol{k}_{\text{sat\_av}}$ is the average of the values of $\boldsymbol{k}$ that satisfied the performance evaluation requirement. Thus, $\boldsymbol{k}_{i+1}$ is an estimate of the mean of the satisfactory cases corrected by the mean of all samples. The expectation of $\boldsymbol{k}_{\text{av}}$ is $\boldsymbol{k}_i$ because it assumes uniform distribution in the search area defined by Eq. (4). The iteration then continues by using $\boldsymbol{k}_{i+1}$ as the next $\boldsymbol{k}_i$. Because the parameters' distribution is uniform, shifting the parameter to the average of satisfactory cases will give a performance improvement if one exists.

Because in general the final mission achievement probability should be high, the number of Monte Carlo simulations must be large enough to ensure reliability of the probability estimate. Furthermore, if the number of satisfactory cases generated at a given iteration of the mean-tracking technique is large, the shift between iterations becomes small, and consequently a large number of iterations are required for convergence on the optimum point. A large computation time is, therefore, implied, and a computation time reduction technique becomes essential to allow use in practical design. One such simple technique is to stress the control system artificially or to omit easy conditions for the control system from the iteration. The details of this technique are as follows:

1) Define the initial $\boldsymbol{k}$ as $\boldsymbol{k}_1$. Monte Carlo flight simulation, in which uncertain parameters $\boldsymbol{x}$ are randomly generated according to the probability distribution functions, continues to find N_1 uncertain parameters $\boldsymbol{x}$ that produce unsatisfactory results. Store this set of N_1 values of $\boldsymbol{x}$ as stressful parameters.

2) Randomly generate a set of N_2 uncertain parameters according to the probability distribution functions. By adding this to the previous set of N_1 stressful parameters, an artificially stressed set of N $(=N_1 + N_2)$ uncertain parameters $\boldsymbol{x}$ is generated. N uniformly random design parameters $\boldsymbol{k}$ are also generated for searching the area around $\boldsymbol{k}_i$ according to Eq. (4).

3) A flight simulation for each $(\boldsymbol{x}, \boldsymbol{k})$ is conducted to see whether it satisfies the requirements. Then $\boldsymbol{k}_{i+1}$ is obtained from the mean of satisfactory cases according to Eq. (5). If there is an unsatisfactory case resulting from a value of $\boldsymbol{x}$ not in the stressful parameter set, the corresponding $\boldsymbol{x}$ is added to the set of stressful parameters, increasing N_1. Continue by returning to step 2 to improve the design parameter.

Some points of discussion remain, such as how to determine the value of $\Delta\boldsymbol{k}$ or how to change it if necessary, how to determine the values of N_1 and N_2, and how to evaluate the convergence. Currently, the value of $\Delta\boldsymbol{k}$ is set a priori by judging the parameter's sensitivity and resolution. Relatively small numbers are used for N_1 and N_2, such as $N_1 = 100$ and $N_2 = 0.2N_1$. Regarding convergence, no stopping condition is set, that is, iteration continues to a prescribed maximum number.

A typical demerit of this approach is that, because it is equivalent to gradient methods, the point converged on might be merely a local optimum rather than the global optimum. Numerical examples obtained by the mean-tracking technique are discussed in the following section.

V. Application to Uninhabited Space Vehicle Flight Control

Miyazawa et al.[5] discussed the longitudinal flight control law design for a space vehicle's automatic landing system, where the probability of satisfying landing requirements and the effects of uncertain parameters were evaluated for the flight control system. That analysis was a product of ALFLEX,[10–15] where 13 successful landing trials were conducted at Woomera, South Australia in 1996. The analysis indicated that Monte Carlo flight simulation is useful for development of robust flight control systems, and in fact, the probability of mission achievement estimated by simulation was able to give the ALFLEX team high confidence of success before the first landing trial was conducted.[7] A sophisticated simulation model was developed for the ALFLEX flight experiment, where the stochastic properties of uncertain parameters were assumed. The uncertain parameters numbered more than 100, and the categories of uncertain parameters and the number of items in each category are listed in Table 1. Typical parameters that had a strong influence on longitudinal landing performance are listed in Ref. 5. The design requirements are listed in Table 2. Figure 4 shows three views of the ALFLEX vehicle.

In Ref. 5, stochastic analysis was extended to a simple design problem, where two proportional and derivative gains in the guidance law were adjusted to maximize the probability of satisfying the landing requirements. Because at that time an appropriate algorithm and sufficient computation resources for stochastic optimization were not available, the number of adjustable parameters that could be optimized was limited, and the optimization was conducted in a primitive way. Since then, a computational algorithm applicable to a large number of design parameters with reasonable computational time has been found, as discussed in the preceding section, and ALFLEX's guidance laws have been again reviewed using this algorithm. The following two applications, longitudinal and lateral guidance laws, are introduced to evaluate the feasibility of the stochastic parameter tuning approach.

Table 1 ALFLEX uncertain parameters

Category	Number of parameters
Mass parameters	5
Aerodynamics	27
Actuator dynamics	9
Sensor dynamics and error	38
Atmospheric condition	6
Initial condition and error at release	18

Table 2 Landing performance requirements

Evaluation point	Guidance, navigation, and control requirement[a]
Touchdown position,[a] m	$X > 0$, $\lvert Y \rvert < 18$
Velocity, ms	$43 < V_{\mathrm{EAS}} < 59$[b]
	$V_G < 62$, $V_{\mathrm{sink}} < 3$
Attitude, deg	$\Theta < 23$, $\lvert\Phi\rvert < 10$
	$\lvert\Psi\rvert < 8$
Sideslip, deg	$\lvert\beta_G\rvert < 8$ (3[c])
Ground roll position, m	$X_{\mathrm{stop}} < 1000$
	$\lvert Y_{\max}\rvert < 20$ (10[c])

[a](X, Y, Z) is a runway coordinate system: origin is at the runway threshold, the X axis is directed along the runway centerline, and the Z axis is directed downward.
[b]Airspeed requirement is excluded from the present study because it is not essential for safe landing.
[c]New requirements set for the present study.

A. Longitudinal Guidance Law Assessment

Longitudinal guidance of a reentry space vehicle before touchdown is susceptible to errors. Figure 5a shows a block diagram of the ALFLEX longitudinal flight control law. Because the reference flight path is curved in the preflare phase before touchdown, longitudinal guidance becomes a tracking problem, and so the guidance command law needs feedforward or open-loop commands to follow the reference path, in addition to the ordinary feedback commands. The feedforward command is generated using nominal vehicle dynamics, and any error in the dynamics causes a disturbance to the longitudinal guidance.

Increasing the bandwidth of the guidance feedback control (or adjusting the feedback gain) to the limit of coupling with the inner-loop attitude control is effective in suppressing such longitudinal guidance error. However, the response of the inner-loop attitude control changes due to uncertain parameters. In most cases, therefore, flight control designers allow some margin for avoiding coupling between the outer and inner loops by predicting the inner-loop control system's deviation using flight simulations. The stochastic parameter tuning method can optimize this design process efficiently, and ALFLEX longitudinal guidance assessment by stochastic parameter tuning demonstrates the feasibility of this method.

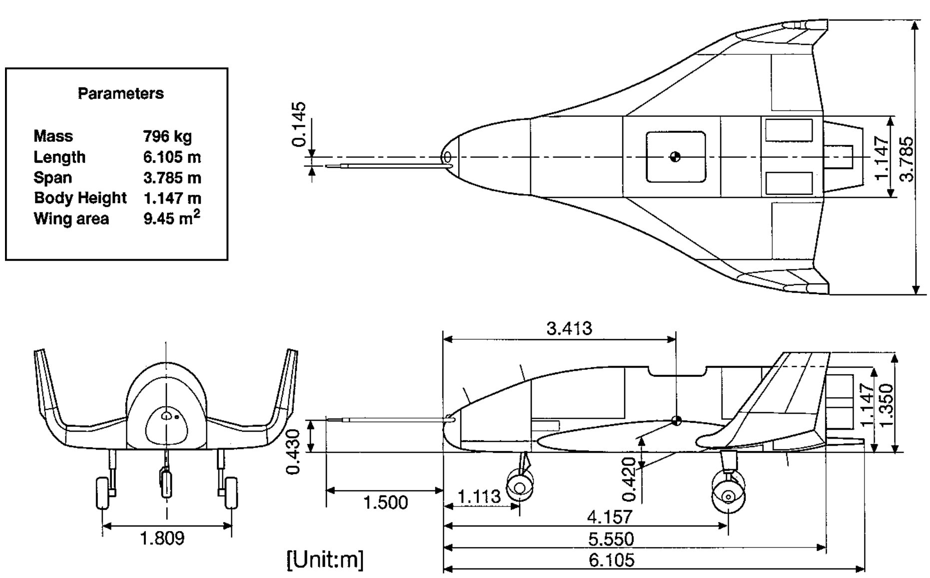

Fig. 4 Three views of ALFLEX vehicle.

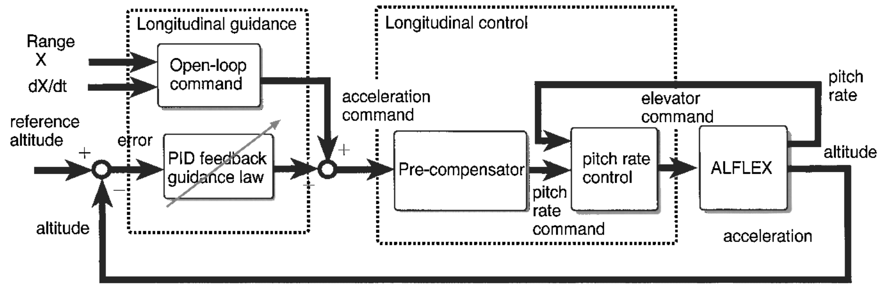

Fig. 5a Simple block diagram of ALFLEX longitudinal guidance and control law: original and modification I.

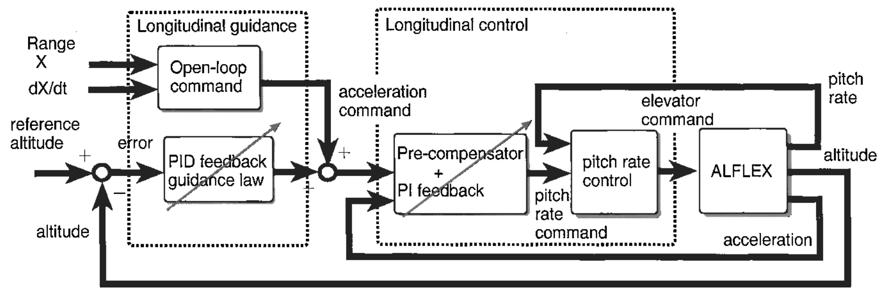

Fig. 5b Simple block diagram of ALFLEX longitudinal guidance and control law: modification II.

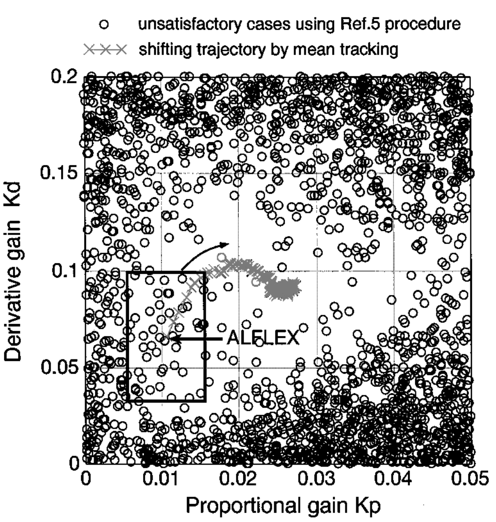

Fig. 6 Optimization of two design parameters for modification I.

1. Modification I

In Ref. 5, a new ALFLEX guidance law, called modification I, was derived from the original by optimizing two proportional–derivative feedback gains. The paper allowed random variation of the two design parameters within the prescribed search area. Of the 10,000 Monte Carlo simulations conducted, 2,122 cases were unsatisfactory, and these are plotted in Fig. 6 as ○ symbols on the plane of the two design parameters. Because the distribution functions of the design parameters are uniform, the sparsest area indicates the optimum design parameter combination, and the design parameters were picked by selecting a point on the plot within such an area, that is, $Kp = 0.027$, $Kd = 0.09$.

In this paper, the same problem is optimized by the mean-tracking method. The mean-tracking method applies a technique similar to Ref. 5, but uses a narrower search area for shifting the design parameters. Figure 6 also shows the history of shifting the design parameters from the original ALFLEX guidance law values by the mean-tracking method with enhanced stress applied to the optimization iteration. The rectangular window in Fig. 6 indicates the search area at the initial parameter point. The same sized search area was used throughout the mean-tracking iterations. This converged almost to the vicinity of the selected point in Ref. 5 after 100 iterations, that is, $Kp = 0.0256$, $Kd = 0.0902$.

2. Modification II

Figure 5b shows a block diagram of the so-called modification II guidance and control law, derived from the original to improve longitudinal landing performance. In this modification, a total of seven design parameters were optimized by stochastic parameter tuning, namely, three proportional–integral–derivative (PID) gains in the guidance feedback control, two proportional–integral gains for acceleration feedback, one final flare gain, and one delay compensation time in the open-loop command generation. Figure 7 compares the landing performance of the vehicle using the original (unoptimized), the modification I, and the modification II guidance laws. Landing performance is shown in terms of touchdown velocity vector, which is the most critical landing parameter, and the plotted circles show the results of 1000 Monte Carlo simulations. The landing performance requirements are also indicated.

Although the original ALFLEX guidance law was carefully designed using extensive trial and error to suppress path-tracking errors, it is clear from Fig. 7 that stochastic parameter tuning gives superior performance. In fact, with the original guidance law, 51 cases of 1000 simulations fail to satisfy the landing requirements, whereas with the guidance law optimized by stochastic parameter tuning, only 1 out of the 1000 simulated trials resulted in violation of the requirements.

B. Lateral Guidance Law Assessment

Because the horizontal component of the nominal flight path is simply a straight line to the runway, lateral guidance becomes a regulator problem rather than a tracking problem as in the case of longitudinal guidance. Furthermore, because bank angle directly generates lateral acceleration, lateral guidance is much easier than longitudinal guidance. Conversely, however, lateral-directional control is more difficult than longitudinal control due to the roll–yaw coupling characteristics of the ALFLEX vehicle.

Monte Carlo simulation analysis showed that the original ALFLEX lateral guidance and control laws had an extremely high probability of satisfying the touchdown requirements, such as maximum lateral deviation on the runway, roll attitude, and sideslip angle relative to the ground. In this analysis, stricter performance requirements are set for the maximum lateral deviation in ground roll and sideslip angle relative to the ground at touchdown parameters, as

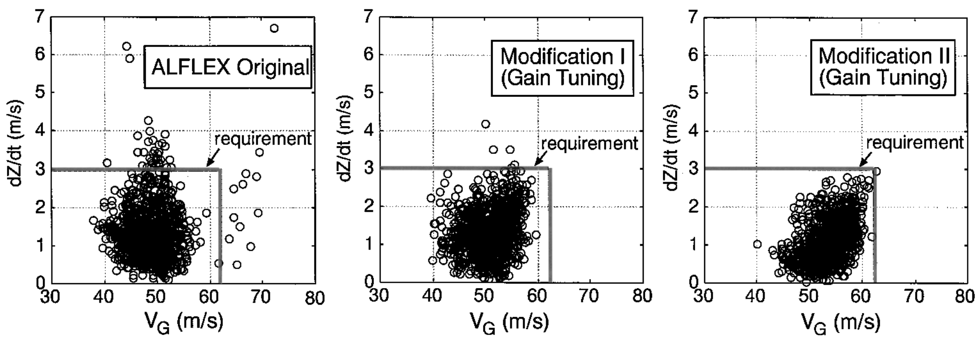

Fig. 7 Monte Carlo simulation: touchdown sink rate and ground speed plot (1000 cases): modification I, two parameters tuned, and modification II, seven parameters tuned.

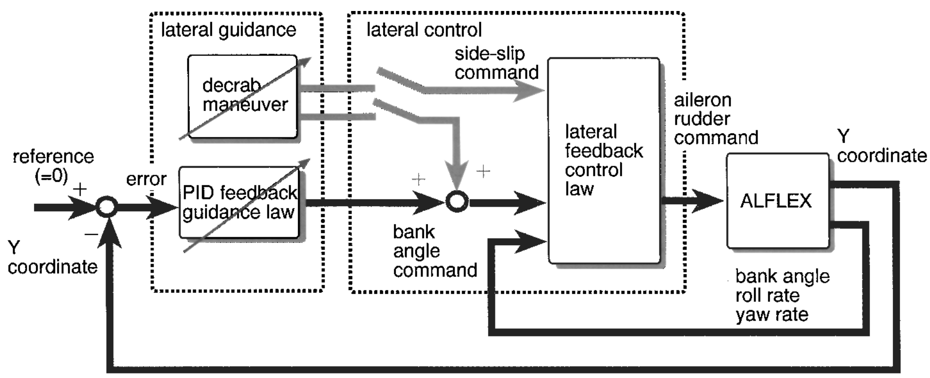

Fig. 8 Simple block diagram of ALFLEX lateral-directional guidance and control law.

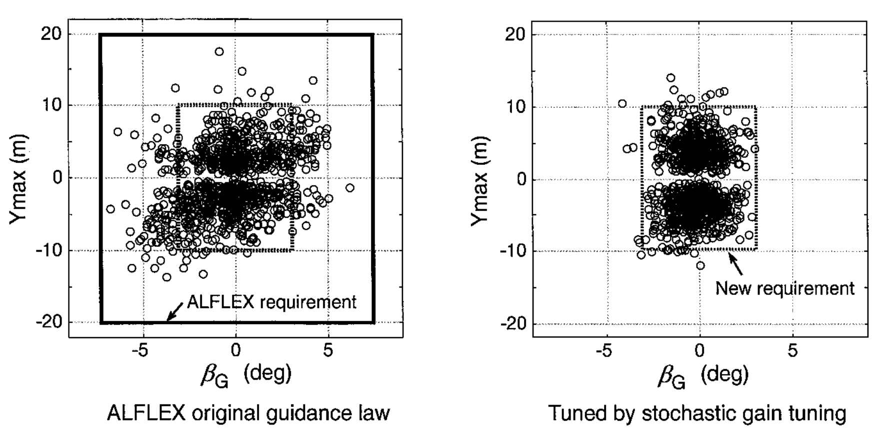

Fig. 9 Monte Carlo simulation: touchdown sideslip angle relative to the ground and maximum lateral deviation in ground roll (1000 cases).

indicated by the numbers in parentheses in Table 2. If the vehicle's performance is able to meet these new requirements, the strength (and thus weight penalty) of its landing gear and its landing runway requirements may be reduced. A design trial with these more stringent lateral requirements was conducted to evaluate the stochastic parameter tuning method.

Figure 8 shows the structure of ALFLEX's lateral-directional guidance and control. The lateral guidance law is essentially a simple PID controller, although it includes limiters such as in the integral feedback and in the bank angle command. To satisfy the new landing requirements, the guidance feedback gains are revised and a decrab maneuver is added. The adjusted parameters are three PID gains, two feedback gains for the decrab maneuver, and the decrab maneuver initiation height. Figure 9 shows the results of Monte Carlo simulation analyses for the original ALFLEX guidance law and the new guidance law optimized by stochastic parameter tuning. For each guidance law, 1000 cases of the same Monte Carlo flight simulations are plotted, and Fig. 9 clearly indicates the superior performance of the optimized guidance law. The number of unsatisfactory cases is reduced to one-fifth of that obtained by the original guidance law. Although the original design is satisfactory and has been verified by flight experiments, the improvement in lateral landing performance will be useful in the future development of reentry space vehicles.

In the two aforementioned application examples, the stochastic parameter tuning method was applied to the guidance law or outer-loop control rather than to the inner-loop attitude control law. This is because the flight simulation model with uncertain parameters represents the vehicle's behavior within the frequency range of rigid-body motions. The results of the tuning of the guidance law are guaranteed within this frequency range. However, to apply the stochastic tuning method to the attitude control law, an uncertainty model is needed for a higher frequency range to include such phenomena as structural vibration modes, unsteady aerodynamics, higher-order actuator dynamics, etc. Although realizing such a simulation model is possible in principle using higher sampling rates, it requires greater computational resources. ALFLEX's attitude control laws were analyzed and designed with robust linear control

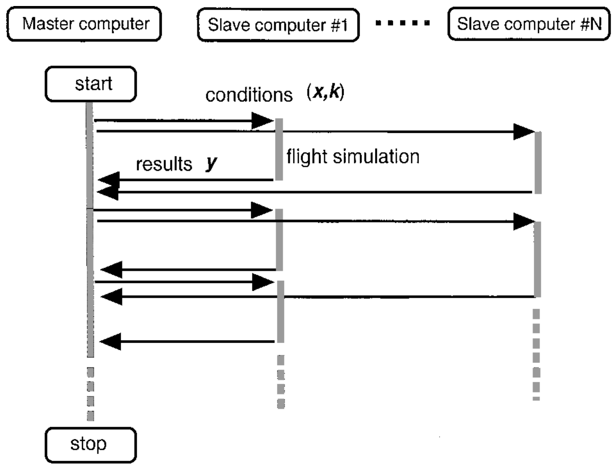

Fig. 10 Schematic flow diagram of distributed computation for Monte Carlo flight simulation.

theory by using high-frequency uncertainty models defined in the frequency domain. Therefore, only the guidance law was tuned by the stochastic method.

Performance improvement as a result of tuning was mainly obtained by increasing guidance gains or by increasing the frequency bandwidth to the limit that does not couple with inner-loop attitude control. If there is ample margin, minor changes in the attitude control law do not affect the outer-loop guidance law, and so guidance and control laws can effectively be designed separately. However, in the case of a high-performance vehicle such as a reentry space vehicle, it is necessary to minimize such a margin, and it is, therefore, reasonable to apply stochastic parameter tuning.

VI. Distributed Computation

The stochastic approach to flight control system evaluation and design requires a huge amount of computation, and this burden is a potential problem when applying the approach to practical flight control design activities. However, the recent advent of low-cost, high-performance microprocessors has greatly reduced the cost of required computing power, and computer network technology can further reduce computation time by allowing distribution of the computational load. Because each Monte Carlo simulation is independent, that is, it is not affected by the results of other simulations, it is amenable to such distributed computation. Moreover, because the quantities of input and output data for each simulation, basically $(\boldsymbol{x}, \boldsymbol{k})$ and $\boldsymbol{y}$, respectively, are small, for example, less than 10 kB, the load on network communication is very light.

Figure 10 shows a schematic diagram of the data flow in a distributed Monte Carlo flight simulation and parameter optimization implementation using a single master computer and an arbitrary number of slave computers. The master computer generates input parameters $(\boldsymbol{x}, \boldsymbol{k})$ and submits them to an idle slave computer, which starts a flight simulation. On completion of the simulation, the result $\boldsymbol{y}$ is returned to the master computer, which stores the input and output data, $(\boldsymbol{x}, \boldsymbol{k})$ and $\boldsymbol{y}$ and calculates probability estimation and parameter optimization.

For flight control design, the authors have developed system software that controls slave machines and manages input/output data transfer using the standard UNIX socket interface over the TCP/IP network protocol. The authors currently use a network of eight twin-CPU workstations (Sun Microsystems Ultrasparc II) as slave computers, or processing nodes. Currently, an efficiency of approximately 75% has been achieved, that is, computation time is $\frac{1}{12}$th of that which would be obtained by serial calculation on a single computer.

VII. Conclusions

Monte Carlo flight simulation analysis has become increasingly important in flight control system development, not only for validating flight control system designs but also for directly designing the adjustable parameters of flight control laws. This paper has proposed and demonstrated the feasibility of a stochastic parameter tuning method that makes full use of the merit of Monte Carlo simulation; that is, the method directly maximizes mission achievement probability, which is the final goal of flight control design.

The effective application of this approach still depends on the judgment of an experienced designer for a few points, such as appropriate design of the guidance and control law structures, the selection of the influential parameters to be optimized, and appropriate choice of the initial parameters for the iteration. In other words, the stochastic approach does not provide a complete set of tools for automated flight control design, but it provides a computer-aided design tool for flight control engineers. In the practical flight control law design process, parameter tuning by trial and error using simulation is common. The proposed approach might essentially do the same, but is more rational, more systematic, and ultimately, as has been demonstrated, more effective.

Application of the approach to real flight control system development would yield further improvements to the design method and further demonstrate its utility. However, flight simulation analysis depends heavily on the assumed model, the stochastic properties of which determine the probability of total mission achievement. Therefore, the model, its structure, and the stochastic properties of the uncertain parameters are the most important factors influencing the method's reliability. Further application of the stochastic approach is, thus, expected to provide strong impetus for improving the fidelity of simulation models and the expression of model uncertainties.

Finally, the authors would like to comment on the role of the stochastic approach in theoretical robust control methods. Because the stochastic approach directly aims at the final design goal, it will be helpful for properly evaluating control theories for the purposes of practical application to flight control. In the future, the stochastic parameter tuning method will be combined with advanced robust control theory and design methods. Then, the stochastic approach will accelerate the realization of more sophisticated laws in flight control systems.

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