88-4123-CP

NLP REENTRY GUIDANCE: DEVELOPING A STRATEGY FOR LOW L/D VEHICLES

Evin J. Cramer*

Boeing Computer Services
Seattle, Washington

Jerre E. Bradt**
John W. Hardtla†

Boeing Aerospace
Seattle, Washington

Abstract

In this paper we discuss problems in developing a strategy for design of a nonlinear programming (NLP) guidance algorithm for a low lift/drag (L/D) reentry vehicle. Two fundamental issues are considered in the design of the guidance algorithm. They are: (1)formulation of the mathematical description of the guidance problem for an NLP guidance algorithm and (2)implementation of the solution of that problem in the flight or onboard computer. This paper considers only the first issue. We show that properly defining the problem is of importance in being able to handle large atmospheric density and wind uncertainties. A method of solution is also presented along with results showing the effectiveness of the algorithm.

Background

In the near future the U.S. will be building a new unmanned launch vehicle capable of lifting heavy payloads that will be designed to complement the space shuttle and existing launch vehicles. One possible component of this vehicle is a reusable propulsion and avionics reentry module that will autonomously return from earth orbit to a specified landing site. This module will contain the rocket motors and the avionics equipment for the launch vehicle. The reentry module will execute a deorbit maneuver and then use aerodynamic forces to fly to the desired landing site. The reusable feature of the reentry module is attractive because it provides a mechanism for reducing launch system costs. However, this will be realized only if the module can be reliably recovered.

The guidance problem for such a vehicle is difficult because it will have limited control (i.e., low L/D), the density and winds along its reentry trajectory are unpredictable, and there will be a high accuracy requirement for reentry and recovery. The low lift to drag ratio characteristics of the vehicle being considered, plus restrictions on the allowed angles of attack, make it likely that using the seasonal mean information on density and winds along the reentry path will be inadequate for final deorbit targeting. To ensure that the reentry module is recovered intact, it may also be necessary to impose heating and structural load constraints along the reentry trajectory. In order to minimize recovery costs, it is desirable to have the reentry module land close to the launch site. The resulting accuracy and range safety requirements impose constraints on the reentry trajectory that must also be considered when making guidance command computations.

General issues that must be considered in designing a guidance algorithm for a specific application are:

(a)Sizing and timing requirements imposed on the flight computer,

(b)Robustness of the algorithm over the total flight regime,

(c)Trades between ground computation vs. onboard computation and targeting,

(d)Advantages of a general algorithm vs. a simplified, specific one.

We are primarily addressing the issue of developing a strategy to increase the robustness of a general guidance algorithm. A thorough discussion of these issues is found in reference 1. Many different guidance algorithms have been studied for reentry. For example, calculus of variation (COV) algorithms have been considered.[2] The Space Shuttle Orbiter entry guidance uses a combination of bank angle and angle of attack to follow a defined drag acceleration profile.[3] In reference 4, the authors discuss their success using a nonlinear programming code for reentry trajectory optimization. In this paper we will extend this idea and use an NLP (nonlinear programming) algorithm as the guidance system for a low L/D reentry vehicle. This discussion will include the development of an NLP guidance strategy for a specific application to aid in the problem formulation.

The precise formulation of the guidance problem for the reentry module is not obvious. A very general definition of the guidance task is to simply find the best way to get the vehicle from its current position to the desired position, but this is much too general to be of any practical use. At any point along the reentry trajectory, there may be many different paths from the current vehicle position to the target. What defines the best path? For some similar applications, minimum time or minimum fuel have been used as the performance index or objective function. Neither of these options seems appropriate for this application. At the other extreme, there may be no physically realizable path between the points. What is the best action to take in this situation? What is the a priori guidance strategy in terms of selection of control

*Principal Engineer, member AIAA
**Senior Specialist Engineer, member AIAA
†Manager, Guidance Technology, senior member AIAA

variables and constraints? These are the questions that we will address.

Solution method

The NLP algorithm is designed to solve a very general problem. Simply stated, the problem is to:

minimize f(X), a scalar function
subject to the nonlinear constraints,
$c_i(X) \geq 0, i = 1,...m$
where X is an n-vector, $X = (x_1,... x_n)$.

There are three major interacting elements in an NLP guidance algorithm. These are the active set strategy, the nonlinear constraint solver, and the unconstrained minimization algorithm. Flight experience with an NLP algorithm is being gained through the application of Gamma Guidance on the Inertial Upper Stage (IUS) orbit transfer vehicle.[5] Figure 1 shows the structure of the Gamma Guidance algorithm. Gamma Guidance has been very effective in its application to propulsive orbit transfers using solid rocket motors. Because of the success of the algorithm on IUS, and the promising results from previous studies on feasibility for applications to aeroassisted orbit transfer vehicles and reentry vehicles,[6,7] we are further refining the algorithm and developing strategies for application to the aerodynamic flight of the reentry module.

The nonlinear programming code used in this analysis was NLP2. For a description of the program methods, active set strategy, constraint solver, and unconstrained minimization techniques, see reference 8. The NLP2 code was designed as an analysis tool and is not suitable for onboard implementation. Considerable development will be required for implementation of the NLP2 components in a flight computer. However, the experience from the successful IUS NLP guidance algorithm provides a significant knowledge base as a starting point for flight code development.

For application to the reentry module, the IUS guidance algorithm and equations will have to be expanded. The addition of inequality constraints requires a more complicated active set strategy. The lack of analytic derivatives of the objective function means that the unconstrained minimization component will have to be modified. The experience gained using the general NLP2 code is valuable in determining which functions of a general NLP algorithm are required to solve the guidance problem. This experience will help to determine the structure of flight code.

The equations of motion implemented in the reentry guidance algorithm include the atmospheric forces and earth's rotational effects. The atmospheric density and east and north components of the wind velocity are input as functions of altitude. The temporal and geographic effects in the wind and density profiles have been taken into account in the generation of the data with GRAM, Global Reference Atmospheric Model.[9] The aerodynamic coefficients are nonlinear functions of angle of attack and mach number.

With this guidance algorithm, the current command depends on a prediction of the future path of the vehicle. Two critical factors in predicting the vehicle path are the atmospheric density and the wind velocity models used by the algorithm. By increasing the prediction accuracy of the guidance algorithm its overall performance can be improved. This prediction includes an estimate of the future guidance commands as well as the vehicle dynamics. We have, however, not simulated any sensor technology nor used any information in predicting the path of the vehicle on board that is not currently available.

Strategy development

The choice of an IUS type algorithm determines the general method of solving the guidance problem once it is defined. The key to making the algorithm work is the definition of a well posed problem. In fact, for this application the answer lies in defining a sequence of problems. At each guidance update the set of guidance control variables that are currently active must be sufficiently large to solve the guidance problem, but at the same time small enough to narrow the possible solution space. The problem definition can vary in response to flight conditions and time in the flight. The problem specification should be sufficiently detailed to be realistic but not so complicated that it makes the optimization problem difficult to solve. The guidance problem for this application is made more difficult because the end constraints are defined by parachute deployment conditions. These are a specific earth relative latitude and longitude at a specified altitude. By the time the vehicle reaches that altitude, it has slowed to the point that there is little aerodynamic control to correct remaining errors.

The general constraints imposed on the the reentry module are:

(a)guide the module to parachute deployment conditions specified in terms of latitude, longitude, and altitude (miss distance = zero)
(b)restrict the angle of attack commands to remain within the structural limits and the stability margins of the vehicle,
(c)limit the reentry flight path so that heating constraints on the vehicle are not exceeded,
(d)limit the maximum loads experienced during reentry,
(e)maintain instantaneous impact point (IIP) within a defined corridor to meet range safety requirements and prevent impact in populated areas.

Constraints (a) and (b), the miss distance and angle limit, are explicitly part of the problem formulation. The algorithm has the capacity to directly handle constraints (c) and (d), the heating and load constraints, but for this study they were not included. Heating and loads were monitored for violation and no problems have been found to date. In the future, these constraints may have to be an explicit part of the problem formulation. Constraints (e), the range safety constraints, have been satisfied by the design of the nominal atmospheric portion of the trajectory. These are gross constraints, not well defined at this time, and therefore difficult to formulate precisely for an optimization algorithm. The deorbit maneuver can be targeted for nominal atmospheric conditions or for selected worst case conditions. We have designed to the nominal and have found in the development of our guidance strategy that the specified guidance accuracy was satisfied for all random atmospheres tested. Further study and analysis of worst case conditions may lead to changes in the targeting strategy.

Constraints are generally dictated by the vehicle and mission to be flown. The actual formulation in the algorithm, however, depends on the coordinate system, choice of state variables, and often, the cleverness of the analyst. Besides the constraint choices discussed above there is also the option of using the terminal miss distance as the objective function to be minimized. A critical step in the development of a guidance strategy is to decide when to add or drop control variables and constraints and when to impose an objective function.

Each guidance update consists of the solution of a two point boundary value problem and a parameter optimization. This means that as part of the guidance algorithm design a parameterization of the control angles must be defined. The boundary value problem is solved using a shooting technique that requires predicting the flight path of the vehicle from its current state to its final state. In other words, the guidance algorithm requires a complete command profile through the atmosphere and nominal atmospheric density and winds along the reentry path. The nominal conditions for the atmosphere can be mean profiles or ones based on ground measurements uplinked to the reentry module prior to the deorbit burn. For this study, we have used seasonal mean profiles for density and wind. Choices for the nominal angle of attack and bank angle profiles depend on range safety, heating, and load limit constraints, as well as the desire to maintain a large margin in total maneuver capability to adjust for the unknown dispersions in density, winds, and vehicle control. Our choice was to center the angle of attack in its restricted range of motion. We programmed a bank reversal maneuver to provide balanced cross range capability. There are many other possible choices for nominal controls and future work will explore the applications of polynomial or other functional forms with functional parameters as control variables.

For our guidance executive, we have set up a hierarchy of problems to be solved. There are no branches on our decision tree If at any time the guidance algorithm fails to find a solution, it will try to solve the next problem in the hierarchy. More levels can be added to the hierarchy if they are needed.

The same algorithm is used from the deorbit burn to parachute deployment to solve a sequence of different problems. For the guidance during the deorbit burn, we solve an underdetermined system of nonlinear equations. The control variables are the ignition time, pointing angles, duration of the deorbit burn, and time to targeted end conditions. The constraints are end conditions on earth relative latitude, longitude, and altitude. A vehicle command profile and nominal atmosphere are specified for atmospheric flight and held fixed. The minimum norm solution is used.

During the atmospheric portion of the flight, bank angle and total angle of attack are used to control the vehicle. The range of angle of attack is limited, as well as, the rates and accelerations on both control angles. Time histories of both angles can be used as control variables. One of the decisions to make when using nonlinear programming, as opposed to a calculus of variation formulation, is how to specify or describe the control time histories. We have found that it is sufficient to divide the atmospheric portion of the flight into three segments. The nominal angles are constant over each segment with a realistic transition at the boundaries. The angle of attack, bank angle, and the length of each segment are all possible control variables. During the early portions of the flight we hold the controls for the final portions fixed during guidance predictions. More controls are only added when they are needed. Miss distance is used as a constraint until it can no longer be satisfied, and then the miss distance objective function is invoked. This strategy ensures that some capability is kept in reserve for uncertainties during the terminal portion of the flight. Again this is similar to Gamma Guidance. The IUS orbit transfer problem is divided into a set of burn and coast arcs. At each arc a different problem can be solved. Early in the flight, burn parameters from the final arcs are not used. Late in the flight when there is little control authority, constraints are dropped.[10]

The design of an active set strategy for a given guidance problem is very important in the design of an effective algorithm. Linear inequalities like the bounds on the control angles are relatively easy to handle. If it is necessary to include the nonlinear heating and load inequality constraints, this portion of the flight code will be more complicated.

Test vehicle and mission model

To demonstrate the application of this guidance strategy, we have selected a specific vehicle model and mission. The vehicle selected is a reentry module with a low lift to drag ratio. The mission is to deorbit from a 150 nautical mile circular orbit at 28.5° inclination, reenter, and guide to parachute deployment conditions specified at a specific earth relative latitude, longitude, and altitude. The reentry vehicle used in this study had a maximum L/D of 0.25 and a reentry ballistic coefficient of 80 lb/ft**2. The nonlinear aerodynamic characteristics used in this study are shown in Figure 2. For a fixed angle of attack the coefficient of lift changes sign as a nonlinear function of mach number. From the figure, it can be seen that a constant angle of attack and constant bank angle will not mean a constant lift direction. The functional form of the aerodynamic coefficients must also be considered in planning a guidance strategy in order to reserve control for the final portion of the flight.

Error sources

In evaluating a guidance algorithm, it is necessary to determine its performance in the presence of error sources of the kind that a vehicle is likely to experience. For the reentry vehicle, these error sources include error in the knowledge of the vehicle's attitude and state, uncertainty in the functional form and magnitude of the aerodynamic parameters, and lack of knowledge about the atmospheric density and wind velocity profiles. Errors in the estimated vehicle state will be small in the era of Global Positioning Satellites (GPS). Attitude errors cause corrective maneuvers commanded by the guidance system to introduce additional errors. There are many techniques for reducing the magnitude of errors in the knowledge of vehicle attitude. These include the use of star scanners[11] and interferometric techniques using the GPS signals.[12] There are also techniques using accelerometer measurements and the predicted and actual maneuver response to correct the estimate of the vehicle attitude.[12] Because these techniques are external to the guidance system, we have not considered their impact on the guidance performance in the results to be reported.

The lack of knowledge of aerodynamic coefficients and atmospheric conditions have similar effect on the performance of the guidance system. In the analysis that follows, we have not attempted to separate the two effects, but have only looked at the guidance response to random atmospheric density and wind velocity profiles. These profiles were generated using the Global Reference Atmospheric Model. We generated random atmospheres for each of the seasons. The general distribution of densities and wind velocities for each season is similar. Figure 3 shows density dispersions from the winter mean and the dispersed winter winds. One hundred random atmospheres generated along a nominal reentry trajectory are shown. To determine if the guidance design was biased to a particular season, a few profiles from each season were selected and flown in the guidance simulation. The results showed no correlation between the guidance response and the season. Detailed analyses were then completed for many atmospheres generated for a single season.

Simulation structure

The general structure of the guidance algorithm was shown in Figure 1. The structure of the guidance simulation used for this study is shown in Figure 4. This is a three degree-of-freedom simulation. The equations of motion used in the NLP guidance algorithm and the vehicle simulation are the same. This includes the coefficients of lift and drag, because we chose not to separate the effects of lack of knowledge of the aerodynamic coefficients and the random density and winds. The atmosphere model in the NLP algorithm was the seasonal mean density and wind velocity profiles. The vehicle simulation used the GRAM generated random atmosphere profiles.

In a real vehicle, there are lags introduced into the system response to commands by the vehicle inertia and finite torques applied to execute commands. In this 3-D simulation, these were modeled by a second order limited response in the execution of angle of attack and bank angle commands. The angular acceleration and rate limits were imposed on both angles. There was also an upper and lower degree limit on the angle of attack. This hard vehicle constraint was implemented as an inequality constraint in the NLP algorithm to insure that no guidance command exceeded the vehicle limit.

Results

As mentioned earlier, the design of the nominal command profiles was determined by a guidance strategy meeting the range safety constraints. These constraints are rough constraints imposed by a landing near the Kennedy Space Center. If there was a malfunction during reentry, the vehicle would spin-up and reenter ballistically. Range safety requires that the ballistic impact points do not fall on populated or designated areas. Figure 5 illustrates the impact that guidance strategy may have on range safety considerations. Figures 5(a) and 5(c) show two potential bank angle command profiles consisting of + and – 90° banks. The order of the commands is reversed in the two profiles with the reversal time adjusted to meet the target conditions. Figures 5(b) and 5(d) shows the trace of instantaneous impact points relative to a coast line and areas to be avoided. In Figure 5(b), the trace approaches one of the forbidden areas. However, a reversal of the order of the bank maneuvers causes the impact trace to shift, avoiding all of the forbidden areas (Figure 5(d)). Issues like range safety requirements can be addressed through adjustments in the nominal command profile developed while planning the guidance strategy for a particular vehicle and mission.

The NLP guidance algorithm worked very well for reentry targeting. The algorithm determines the ignition time, pointing angles, duration of the deorbit burn, and end time for a propulsive maneuver to meet earth relative end condition constraints on latitude, longitude, and altitude. This problem is similar to the orbit transfer problem with the most notable difference being the inclusion of atmospheric effects. During the guidance computations for the deorbit burn, the atmospheric guidance parameters are held constant, and seasonal mean density and wind profiles along the reentry path are utilized. Typically less than five iterations were needed for the algorithm to converge to a solution.

We simulated numerous guided flights through different GRAM generated atmospheres. Figure 6 shows the wind and command profiles for a series of tests to illustrate our guidance strategy and show some of its benefits. Recall, that the same nominal commands are used for all flights. The deorbit burn is adjusted using the mean atmosphere for different seasons. Figure 6(a) shows the nominal commands and the seasonal mean wind magnitude. The atmospheric guidance is initiated at an altitude of 400,000 feet. If at this point the module had perfect knowledge of the conditions it would encounter, then the command profile would change as shown in Figure 6(b). Almost all the correction was accomplished by changing the angle of attack for the early portion of the flight from 10° to 5°. Figure 6(c) is the guided response, using our multi-level strategy, to the same atmosphere as used for Figure 6(b). Figure 6(d) shows the commands from a test where instead of our strategy, all the control variables, i.e. angles and times, were used by the optimizer starting at 400,000 feet. The angle of attack below 100,000 feet was closer to the lower limit of zero than for the run using our strategy. This implies that there is less capability retained to compensate for unknowns. To verify this claim we introduced large wind dispersions between 40,000 and 30,000 feet, on the order of the largest that we saw in all our statistically generated cases, and tested the two strategies. Our multilevel strategy still reached the parachute deployment conditions within the required accuracy, whereas the other strategy did not. The guided trajectories were about evenly divided among those that drove the angle of attack to its lower bound during the final phase, those that drove the angle of attack to its upper bound during the final phase, and those that stayed away from the boundaries. Figure 7 shows wind and command profiles for a case where the angle of attack went to its upper limit of 20°. The entire aerodynamic range of the module is needed to achieve the required accuracy. Therefore it is critical that this resource be conserved along the flight path.

Summary

We have shown that the guidance strategy is important for making the algorithm work well. Using a multi-level strategy, we were able to use the NLP guidance algorithm and obtain effective performance for a low lift reentry module in response to severe atmospheric dispersions and winds. We have not exhausted the possibilities available in the implementation of the guidance algorithm. One option for a continuing effort is to experiment with different objective functions, such as, minimizing the deviation of angle of attack from a nominal profile, maximizing maneuver energy at low altitude, or minimizing fuel for maneuvers. Another option is to experiment with different parameterizations for the nominal control profile. We also will more fully develop the guidance executive that automatically adjusts the problem formulation in response to the sensed flight conditions.

References

1. Hardtla, J.W., Piehler, M.J., and Bradt, J.E., "Guidance Requirements for Future Launch Vehicles," AIAA-87-2462, AIAA Guidance, Navigation and Control Conference, August, 1987.

2. Baker, C. D., Causey, W. E., and Ingram, H. L., "Mathematical Concepts and Historical Development of the MASCOT Guidance Technique for Space Vehicles," NASA Technical Memorandum, NASA TM X-44408, (1971).

3. Harpold, Jon C., and Graves, Charles A. Jr., "Shuttle Entry Guidance,", The Journal of the Astronautical Sciences, Vol XXVII,No. 3, pp. 239-268, July-September, 1979

4. Hull,David G.,and Speyer, Jason L., "Optimal Reentry and Plane Change Trajectories," The Journal of Astronautical Sciences, Vol. XXX, No. 2, pp. 117-130, April June 1982

5. Hardtla, John W., "Gamma Guidance for the Inertial Upper Stage (IUS)," AIAA, 78-1292, August, 1978.

6. Bradt, J. E., Hardtla, J. W., and Cramer, E. J., "An Adaptive Guidance Algorithm for Aerospace Vehicles," AIAA Guidance, Navigation &Control Conference, 85-1917.

7. Bradt, J. E., and Andrews, D. G., "Impact of Upper Atmosphere Density Distribution on Aeroassisted Orbit Transfer Vehicle Design," 35thCongress Of the International Astronautical Federation, IAF-84-435,1984.

8. Betts, John T., "Nonlinear Programming Algorithm NLP2," TOR-0088(3444-04)-1, The Aerospace Corporation, El Segundo ,CA, June 1987

9. Justus, C. G., Fletcher, G. R., Gramling, F. E., and Pace, W. B., "The NASA/MSFC Global Reference Atmospheric Model - MOD 3 (With Spherical Harmonic Wind Model), NASA Contractor Report 3256, (1980).

10. Hardtla, John W., and Schultz, Loren A. "Inertial Upper Stage (IUS)Adaptability Via Gamma Guidance Software Menu Tables,"Annual Rocky Mountain Guidance and Control Conference,82-023,February 1982

11. Tillotson, R., Treder, A., Norris, R., and Scott, P., "Inertial Upper Stage Attitude Initialization and Update on Space Shuttle," presented at the National Aerospace Meeting of the Institute of Navigation, March 1982.

12. Upadhyay, Triveni N, and Rhodehamel, Harley W., "OMV Attitude Update Using GPS: Feasibility Study," MCC-R-88010, February 1988,Mayflower Communications Company, Inc., Wakefield, MA.

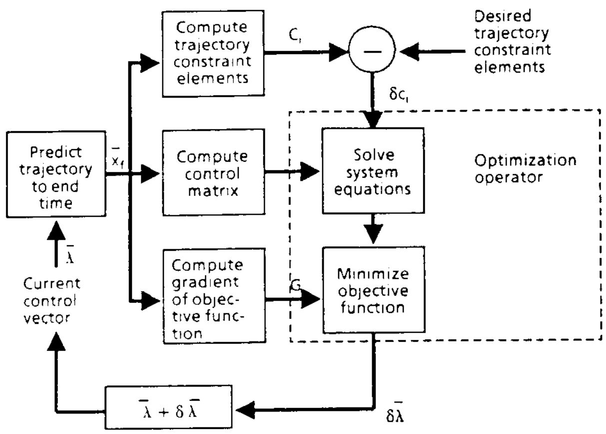


Figure 1. IUS Gamma Guidance structure.

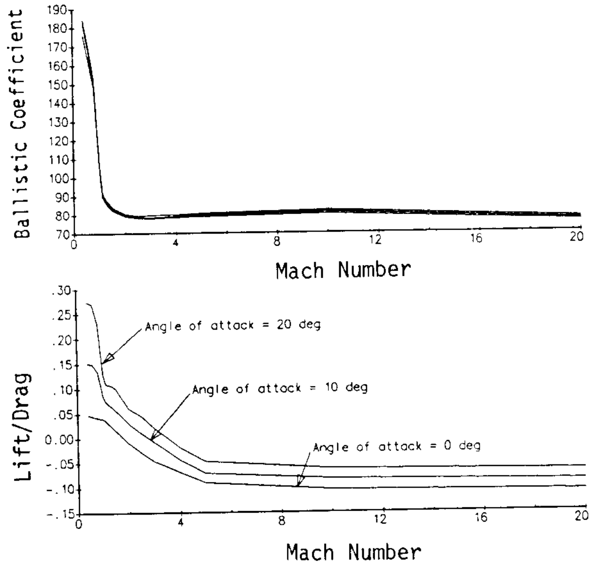


Figure 2. Reentry vehicle aerodynamic characteristics.

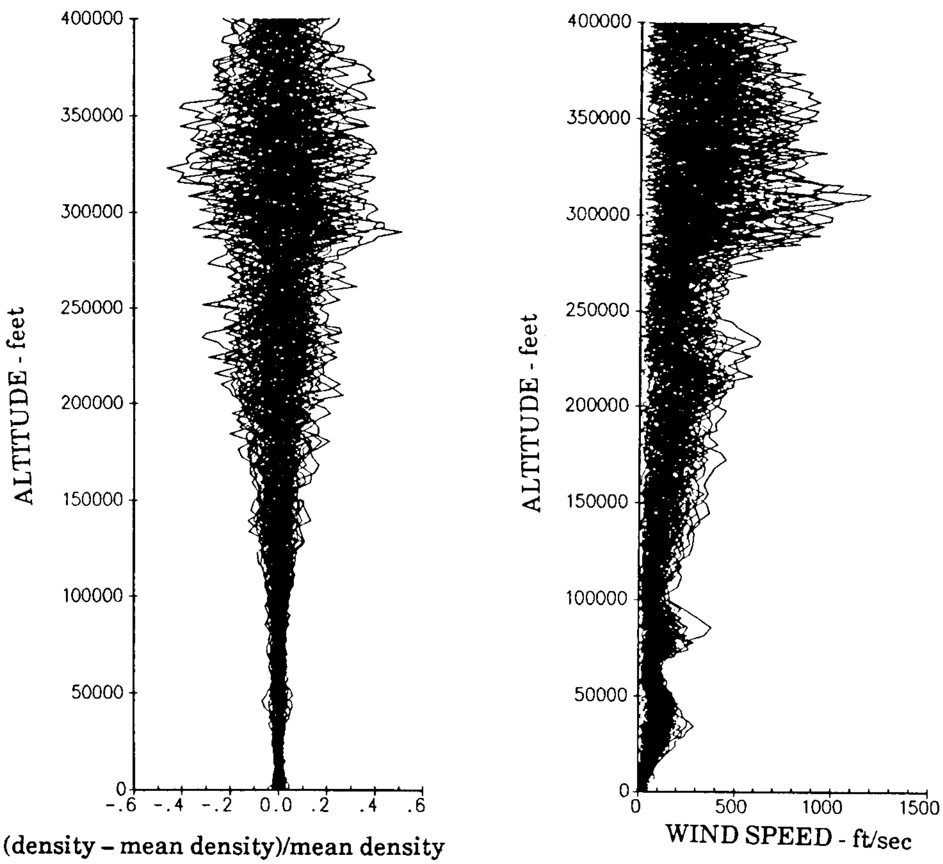


Figure 3. Winter density and wind dispersions from GRAM.

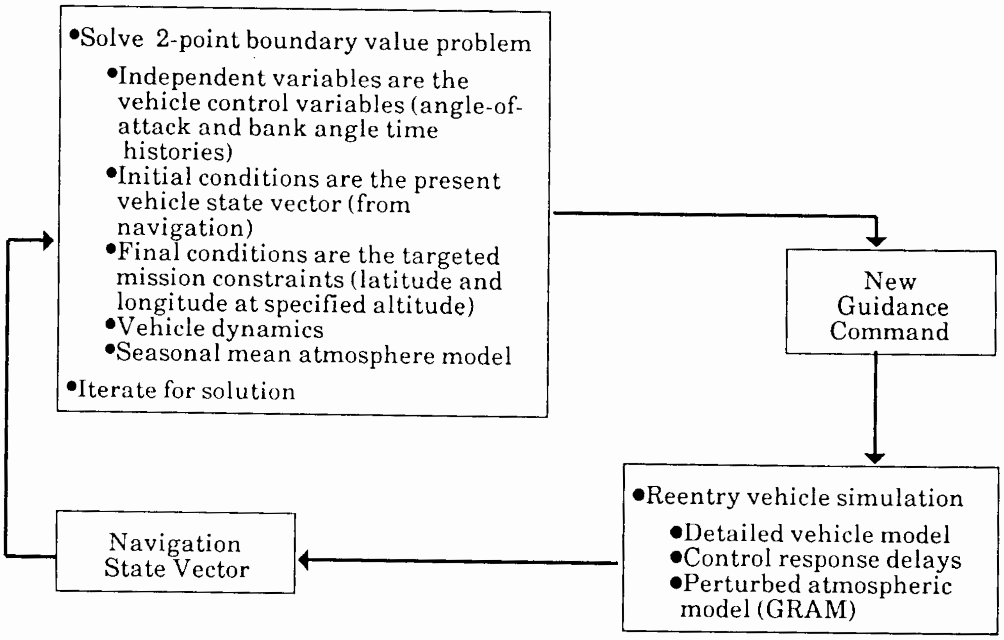
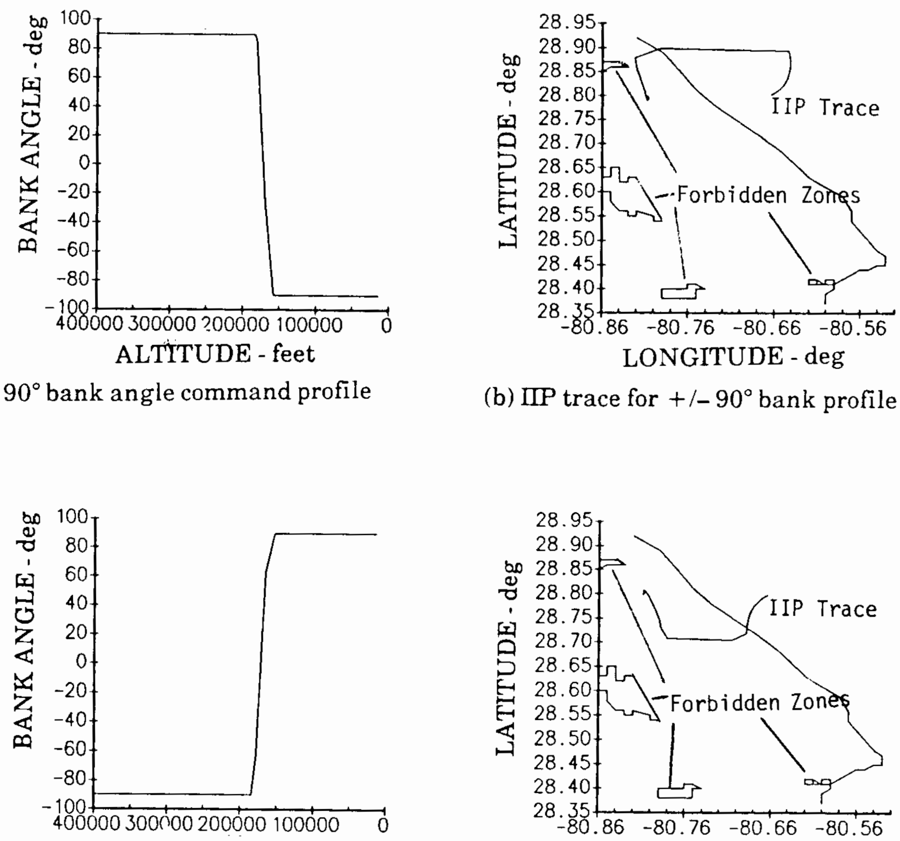


Figure 4. Guidance simulation structure.



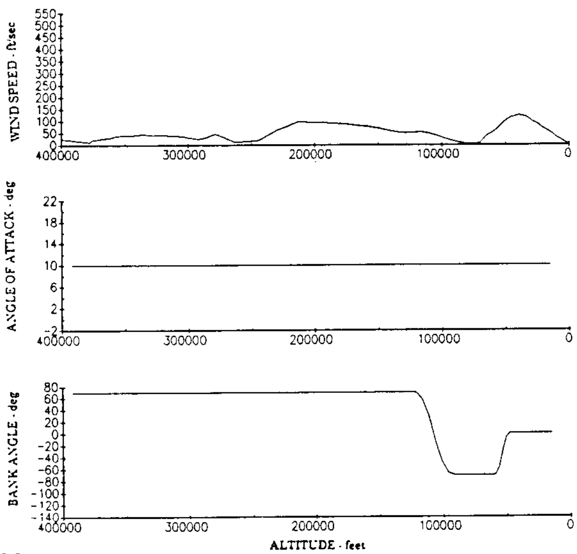
(a) +/− 90° bank angle command profile

(b) IIP trace for +/− 90° bank profile

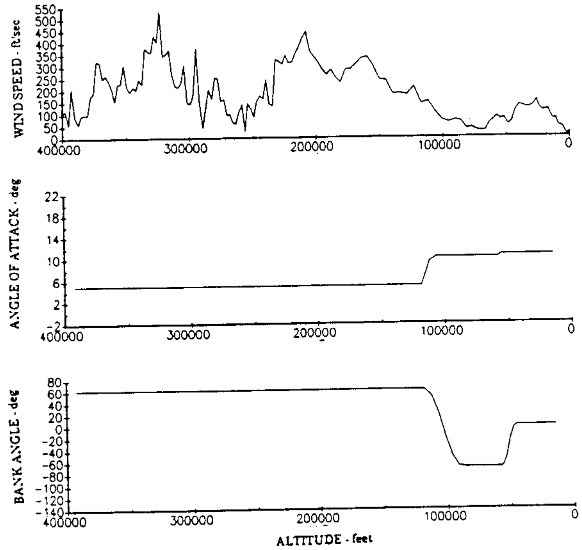
(c) −/+ 90° bank angle command profile

(d) IIP trace for −/+ 90° bank profile

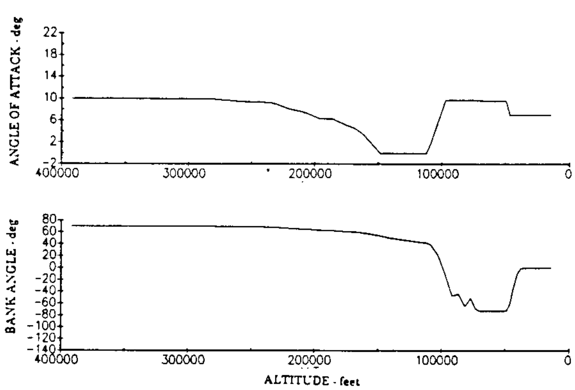
Figure 5. Guidance strategy for range safety.



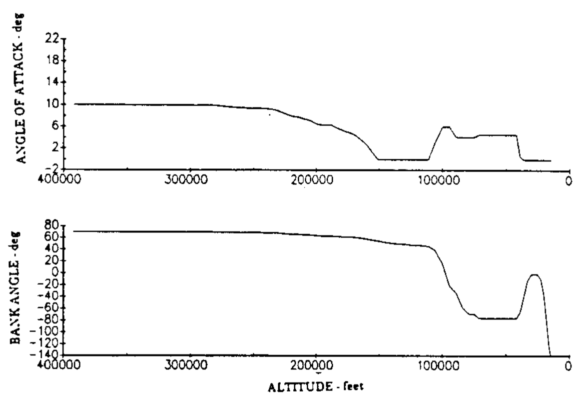
(a)Nominal commands for seasonal mean atmosphere



(b)Perfect command profile for dispersed atmosphere



(c)Guidance command profile for dispersed atmosphere (Multi-level strategy)



(d)Guidance command profile for dispersed atmosphere (all control variables used)

Figure 6. Guidance strategy development.

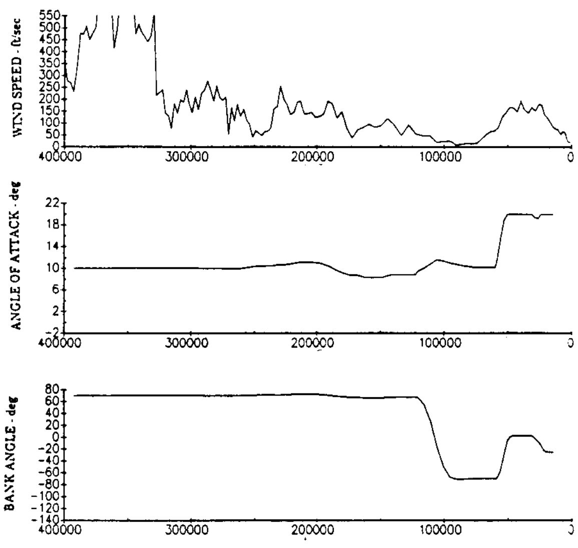


Figure 7. Wind and command profiles with angle of attack limited.