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Robust Flight Path Determination for Mars Precision Landing Using Genetic Algorithms

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ABSTRACT

This paper documents the application of genetic algorithms (GAs) to the problem of robust flight path determination for Mars precision landing. The robust flight path problem is defined here as the determination of the flight path which delivers a low-lift open-loop controlled vehicle to its desired final landing location while minimizing the effect of perturbations due to uncertainty in the atmospheric model and entry conditions. The genetic algorithm was capable of finding solutions which reduced the landing error from 111 km RMS radial (open-loop optimal) to 43 km RMS radial (optimized with respect to perturbations) using 200 hours of computation on an Ultra-SPARC workstation. Further reduction in the landing error is possible by going to closed-loop control which can utilize the GA optimized paths as nominal trajectories for linearization.

1. INTRODUCTION

In this study, GAs are applied to optimizing a nonlinear simulation of descent dynamics of a low-lift vehicle during planetary (i.e., Mars) entry. The basic idea is to find a flight path which comes closest to a desired landing position, yet is robust to expected perturbations in the trajectory. Such a ***robust*** flight path is found by minimizing a quadratic cost function representing the landing miss distance, over several realistically perturbed trajectories. The most important perturbations are the error in the initial entry conditions, and uncertainties in the atmospheric density. In order to vary the flight path, the initial flight path angle is chosen as a free parameter, and the vehicle angle-of-attack is controlled as a function of time. The control of the angle-of-attack is accomplished using the center-of-mass (COM) relocation concept put forth by D. Boussalis of JPL [1]. The COM relocation concept is important because it allows considerable control authority during the atmospheric entry phase to minimize landing errors, yet it is applicable to low-lift Mars Pathfinder type aeroshells (i.e., with lift-to-drag ratio $L/D = 0.3$). This avoids the need for designing higher lift (and much more expensive) vehicles. For simplicity the entry dynamics have been restricted to planar motion, and the landing error is defined at 10 km altitude where the parachute opens rather than at ground level. This paper is an abridged version of a longer report [11].

2. CONTROL ACTUATION

The control actuation scheme will be based on center-of-mass (COM) relocation, as outlined in Boussalis [1]. In this approach, a proof-mass is moved inside the vehicle so that the COM is relocated as a known function of time. The COM relocation acts to shift the dynamic equilibrium of the vehicle such that the angle-of-attack is changed. In particular, the equilibrium angle-of-attack value varies as an explicit known function of the COM relocation. Hence, even though one is moving a proof-mass, the control can be thought of as commanding a desired angle-of-attack. Since the angle-of-attack acts to change the amount of lift or drag on the vehicle, it provides a means to effect the propagation of the flight path.

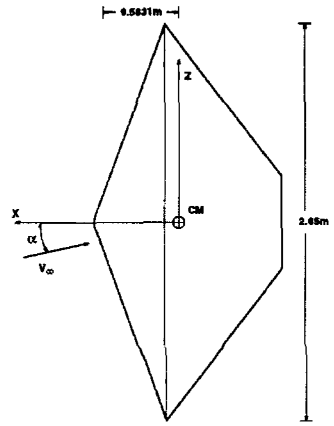

Figure 1 Low lift Mars Pathfinder type aeroshell

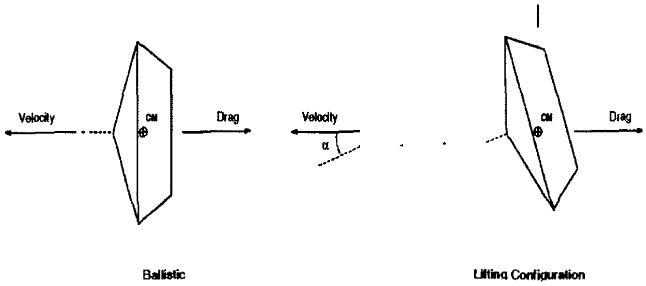

Figure 2 Center-of-mass relocation scheme to control lift vector

3. ROBUST FLIGHT PATH PLANNING MODEL

For the purposes of this study, the "landing error" is defined as the RMS error in the desired terminal ground track location over a collection of 5 simulated paths, i.e.,

$$J = \sqrt{\sum_{i=A,B,C,D,E} \left(S_{xd} - S_{xi}\right)^2 + \left(S_{yd} - S_{yi}\right)^2} \qquad (1)$$

where S_{xd}, S_{yd} (specified later) are the desired ground track at the terminal time, and S_{xi}, S_{yi} are the actual ground track at the terminal time.

For the purpose of evaluating the RMS error ***J, the*** 5 simulations (A, B, C, D, and E) are performed per control profile to determine the effect of perturbations on the flight path. Parameter perturbations associated with A, B, C, D and E are shown in Table 1 and Figure 3. These perturbations reflect the major sources of error in the descent phase which are due to ***uncertainty*** in the atmospheric parameter beta, and uncertainty in delivery to the specified initial flight path angle gamma(0) (i.e., the entry corridor).

Three scenarios are addressed for optimization of the flight path:

Scenario 1: Two Point Boundary Value Problem. Constant Control
Find the control (i.e., the entry condition gamma0, and fixed COM offset dz) that under perfect knowledge and no disturbances, places the vehicle at the desired final position (in terms of its desired ground track) at the terminal time (i.e., the time instant at which the altitude is 10 km, and the parachute deploys). Apply this control to the 5 perturbed trajectories to calculate RMS landing error ***J.***

Scenario 2: Robust Flight Path Determination. Constant Control
Find the control (i.e., the entry condition gamma0, and fixed COM offset dz) that optimizes the RMS landing error ***J*** at the terminal time over the 5 perturbed trajectories.

Scenario 3: Robust Flight Path Determination. 5th Order Control

Find the control (i.e., the entry condition gamma0, and the COM offset dz as a 5th order Chebchev polynomial function of time dz=u(t)=Trun[a0+a1*c1(t)+...a5*c5(t)]), that optimizes the RMS landing error *J* at the terminal time over the 5 perturbed trajectories. Acontrol contraint on dz to +/-.08 m is enforced by the operator Trunc[], which truncates the Chebychev polynomial when it exceeds these thresholds.

Note that by minimizing the RMS landing error *J*, one is not only delivering the vehicle to its desired final position under nominal conditions, but is also minimizing the effect of perturbations on the actual flight path. This is the essence of the robust flight path planning problem.

Table I Perturbed Parameters for Simulation

Indv Runs	beta	gamma(o)
A	1.00*beta0	gamma0 + 0.0
B	1.25*beta0	gamma0 + 0.2
c	0.75*beta0	gamma0 + 0.2
D	0.75*beta0	gamma0 -0.2
E	1.25*beta0	gamma0 -0.2

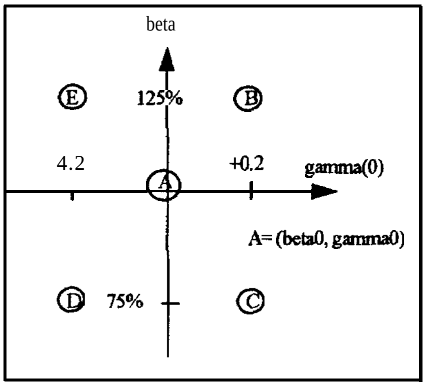

Figure 3 Flight path angle (gamma0) and atmospheric (beta) perturbations

The kinematics and dynamics of the vehicle. during descent are described by the a system of differential equation which can be found in [1][11].

4. GENETIC ALGORITHM IMPLEMENTATION

The Genetic Algorithm Toolbox [7] is used to solve the three scenarios posed in the previous section. For this purpose, the chromosomes are set up as shown in Table 2 and the initial conditions are given in Table 4. The desired final landing location is specified as, $S_{xd} = 556.1$ km and S_{yd} = *976.65 km.*

Table 2 Chromosome Coding

Chromosome	Range value	Precision
gamma0 (degree)	-9 to -17	15 bit
dz (m)	-0.08 to 0.08	15 bit
ai, i=0,...,5	-0.08 to 0.08	15 bits

Table 3 Summary of Computational Requirements

Scenario	# Individuals per population	# Generations	Machine	Memory RAM	Speed	Hours
I	10	20	Pentium	16 Meg	133 Mhz	172
II	20	27	Ultra SPARC	132 Meg	143 Mhz	90
III	20	60	Ultra SPARC	132 Meg	143 Mhz	200

Table 4 Initial States (all scenarios)		
Altitude	125.0	kilometer
Longitude theta	0.0	degree
Latitude phi	-10.0	degree
Velocity	7.5	kilometer/sec
Flight path angle, gamma0	Evolved	degree
Azimuth (heading) angle, psi	60.0	degree
Pitch rate, q	0.0	degree/sec
Pitch	gamma0+alpha0	degree
alpha0	$-C_{m0z} * dz(0) / C_{ma}$	degree
Sx Ground track	0.0	kilometer
Sy Ground track	0,0	kilometer

5. ANALYSIS OF THE RESULTS

The results of all three scenarios are tabulated in Table 5.

Table 5 Summary of Results

	gamma0 (degree)	dz (cm)	Landing Error - RMS Radial (km)
Scenario I	Evolved -12.54	Evolved - 0.03713	111.68
Scenario II	Evolved -13.58	Evolved - 0.0610	75.825
Scenario III	Evolved -12.5080	Chebychev a0 = 0.0145 al = 0.04096 a2 = -0.0690 a3 = 0.0260 a4 = 0.0530	43.3855

For comparison purposes, the landing error plots for Scenarios I,II and III are organized from left to right in *Figure 4*. As expected the RMS landing errors decrease from left to right with increasing control authority.

a. Scenario I b. Scenario 11 c. Scenario 111

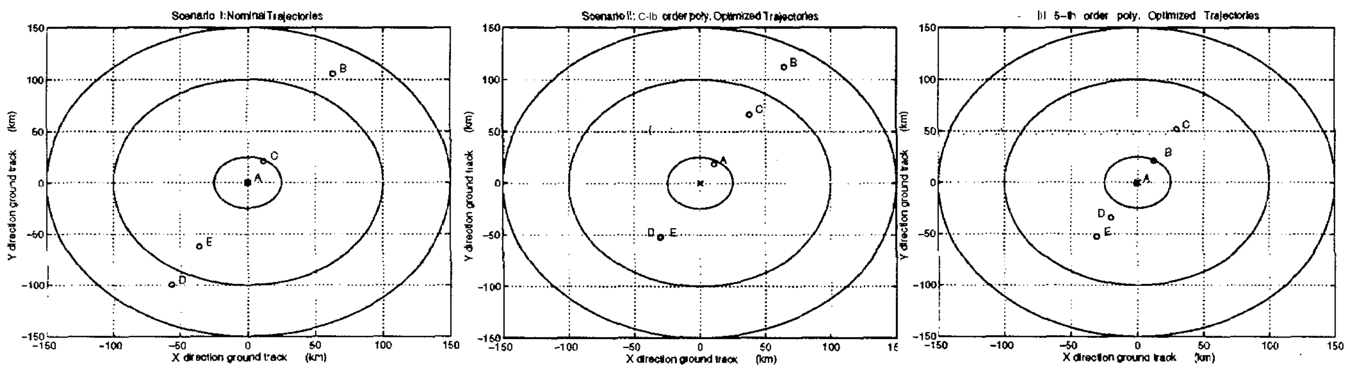

Figure 4 Summary of landing errors for all scenarios

The improvement in going from Scenario I (111 km) to Scenario II (76 km) is to be expected since Scenario I was not optimized with respect to the perturbed trajectories while Scenario II was. The improvement in going from

Scenario II (76 km) to Scenario III (43 km) is also expected since Scenario III is a generalization of Scenario II in terms of progressing from a zeroth order polynomial to a 5th order polynomial control representation.

a. Scenario I b. Scenario II c. Scenario III

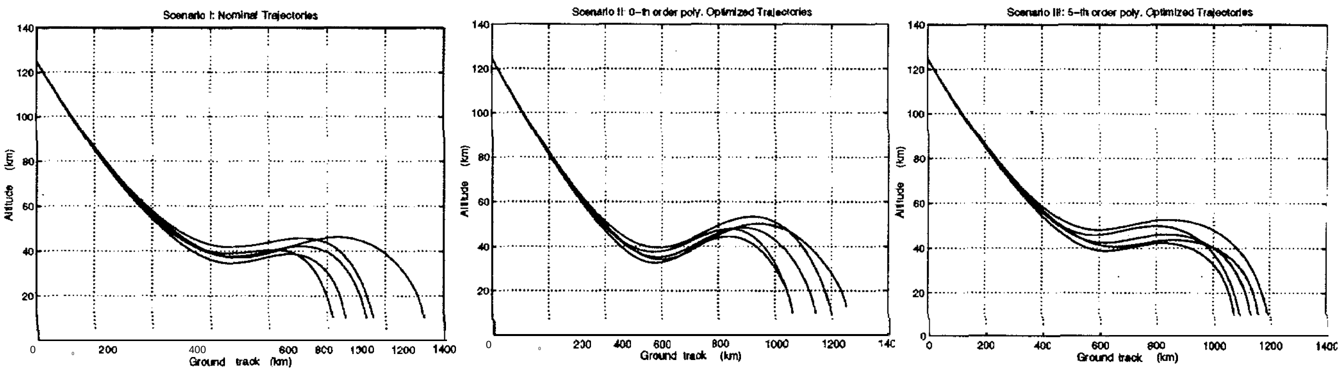

Figure 5 Summary of altitude paths for all scenarios

It is instructive to compare the altitude plots of the three Scenarios in Figure 5. It is seen in Scenario III how the GA successfully reduces landing error by making the perturbed flight paths coalesce.

The flight path determined by GA for the 43 km (Scenario III) result is very interesting and suggests a new “bounce and plop” strategy for precision landing. In order to study this strategy in more detail, the altitude and control signal dz=u(t) for Scenario III are plotted on the same x-axis (i.e., versus time) in Figure 6. The scale for the control signal has been converted to mm to allow sharing of the same y-axis. It is seen that the “bounce” is induced by lowering the COM (i.e., dz=u(t)) to its maximum negative location of u= -.08 m (i.e., maximum positive lift), at approximately 10 seconds. Note that the bounce does not take effect until the atmosphere is sufficiently dense at an altitude of 40 km (occurring at approximately 75 seconds), to create a significant lift effect. The “plop” is induced by raising the COM location to its maximum positive location of u= +.08 m (i.e., maximum negative lift), at approximately 135 seconds. Again, the negative lift is seen to take effect when the atmosphere becomes sufficiently dense at an altitude of 40 km (occurring at approximately 200 seconds). This overall approach forces the perturbed trajectories to coalesce, which effectively reduces landing error.

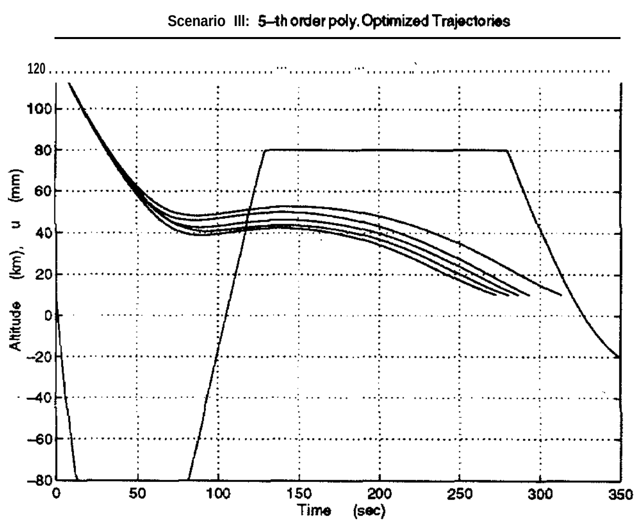

Figure 6 Superposition of vehicle altitude and control signal dz=u(t)

6. CONCLUSIONS

A genetic algorithm was applied to the problem of robust flight path determination for Mars precision landing. The notion of a robust flight path appears to be new, although it is a natural statement of what is desired in many open-loop control scenarios. In this study, the objective of the robust flight path problem was to determine the flight path which delivers a low-lift open-loop controlled vehicle to its desired final landing location while minimizing the effect of certain realistic perturbations.

The results of the study can be summarized as follows. When the control (i.e., the COM location) is chosen constant with time and the flight path is optimized with respect to the nominal trajectory, the resulting landing error is 111 km RMS radial. When the control is chosen constant with time and the flight path is optimized over perturbed trajectories, the landing error is reduced to 76 km RMS radial. When the control is allowed to vary as a fifth order polynomial and the flight path is optimized over perturbed trajectories, the landing error is 43 km. The trajectory determined by GA for the 43 km result is very interesting and suggests a new "bounce and plop" strategy for landing.

The major computational bottleneck for this study was in evaluating the objective function (or equivalently, the "fitness") for each individual in the population, since it required integrating the kinematics and dynamics of motion. For implementation purposes, it was necessary to trim down the GA implementation to a reduced population of 20 individuals and no more than 60 generations, requiring approximately, 20*10*60/60=200 hours of computation on an Ultra SPARC computer. Methods to reduce the computation time would be greatly beneficial.

Results indicate that even though genetic algorithms may require long processing times, they are fairly easy to program, and can provided useful solutions to complex optimization problems, such as those associated with problems of robust flight path planning, and spacecraft autonomy.

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