



On-board Autonomous Attitude Maneuver Planning for Planetary Spacecraft using Genetic Algorithms

Richard P. Kornfeld

*Jet Propulsion Laboratory,
California Institute of Technology,
Pasadena, CA, 91109*

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Content



- The Nature of the Problem
- Existing Approaches
- Approach to Path Planning
- Why GAs ?
- Cost Function Formulation
- Encoding
- Case Example I: Europa Orbiter during Cruise
- Case Example II: Europa Orbiter in Europa Orbit
- Summary & Conclusions
- References



The Nature of the Problem



- For a spacecraft in interplanetary cruise:
 - **time-fixed** boundary conditions: initial and final attitude are not a function of time
 - **time-fixed** constraints: constraints are static
- For a spacecraft in orbit or during flyby:
 - **time-varying** boundary conditions: initial and final attitude are a function of time
 - **time-varying** constraints: constraints change as a function of time

• Types of constraints

–geometric constraints:

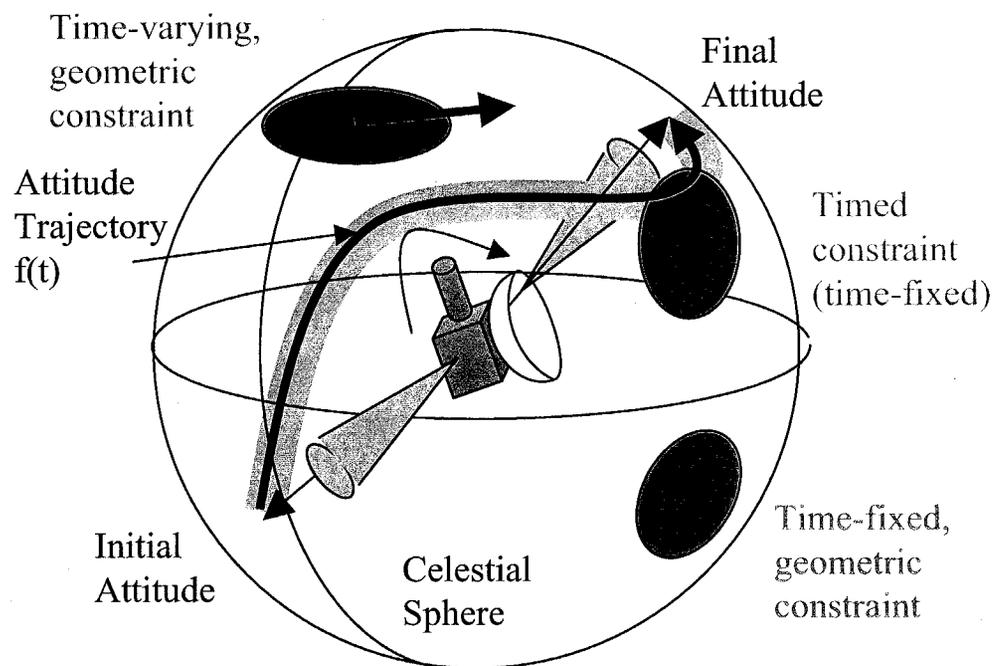
angular separation between body vector x and celestial vector y shall never be less than δ (e.g. star tracker, science instrument boresight)

–timed constraints:

angular separation between body vector x and celestial vector y shall never be less than δ for a time period greater than T (e.g. power, thermal constraints)

–dynamic constraints:

spacecraft turn rates and accelerations shall be smaller than ω_{max} and a_{max} , respectively (e.g. limited star tracking capability or control authority)





The Nature of the Problem



- Robotics Heritage:
 - Determining a constraint free attitude maneuver is closely related to the task of navigating a robot in the presence of moving obstacles and robot dynamics (*kinodynamic planning*).
 - ⇒ Concepts and approaches developed for autonomous robot motion planning are applicable to the spacecraft attitude maneuver planning problem.
- Computational Complexity:
 - Even the simple problem of navigating a kinematic robot in a known environment with polyhedral obstacles has been proven to be computationally hard [1,2].
 - When the dynamics of the vehicle are also considered, there is strong evidence that the computational complexity of a complete algorithm will grow exponentially fast in the number of dimensions of the *state space*.
 - ⇒ Autonomous path planning with moving obstacles is generally considered to be a computationally hard problem (robotics heritage).
 - Even though *complete* algorithms are available, these cannot be used for real-time path planning in many real-world applications [1].

[1]Canny, J.F., "The Complexity of Robot Motion Planning", MIT Press, Cambridge, MA, 1988.

[2]Latombe, J.C., " Robot Motion Planning", Kluwer Academic Publishers, Boston, MA, 1991.



Existing Approaches

- Topex Autonomous Maneuver Experiment (TAME):
 - Iterative walk-around (undirected trial-and-error based) with two turns
 - Not suited for moving constraints
- Cassini Constraint Monitor:
 - The Cassini Constraint Monitor (CMT) *autonomously checks* the commanded attitude trajectory for any constraint violation and, if necessary, *modifies* commanded turn profile to be compliant.
 - ⇒ CMT has limited planning horizon (4 seconds) and acts thus *retro-actively*.
- The DS-1 spacecraft used an Attitude Planning Expert (APE) to autonomously turn the spacecraft. It was an off-line tool (i.e. non-real time) to determine the feasibility of a turn. It consists of
 - a simple attitude commander with no constraints avoidance planning capability and
 - a Cassini-type Constraint Monitor



Approach for On-Board Attitude Maneuver Planner



- ⇒ Primary objective is to obtain a *feasible* solution in a *reasonable* time
 - ⇒ Reduce the problem to be computationally tractable!
 - ⇒ Trade-off between optimality and computational complexity
- Simplify the problem to the greatest extent possible while maintaining the validity of the model:
 - e.g omit non-relevant spacecraft dynamics
- ‘Customize’ the problem:
 - e.g. define limited, convex attitude maneuver space (e.g. DS-1)
 - e.g. define limited set of possible attitude turns
 - ⇒ Trade-off between up-front customization and level of flexibility
- Over-constrain the problem to account for uncertainties
- Incorporate constraints into cost-function to convert it from a constraint to an unconstrained optimization problem
- Using (global) random search techniques, search for and, if found, optimize attitude trajectories that minimize the cost-function
- ⇒ Use solution ‘as is’ or as an initial condition to initialize additional deterministic optimization algorithm



Why Genetic Algorithm (GA) ?



Current motion planning approaches can be divided in:

- Heuristic Methods
 - Variational methods
 - Potential field methods
- Enumerative Methods
 - Exhaustive search
 - Dynamic programming
- Random Search or Probabilistic Methods
 - **Genetic Algorithms** →
 - Simulated Annealing
 - Rapidly Exploring Random Trees
 - Probabilistic Roadmap Planner.
- Use a hybrid approach based on a combination of the above

- Directed random search of a large solution space
- Easy and fast to implement
- Constraints on control and state-variables can be incorporated readily
- Many successful applications
- Suited for discrete events such as thruster firings
- Highly parallelizable



Simplifications for this Study



- ⇒ Used EO spacecraft and EO ACS requirements as a baseline for this study.
- Considered only spacecraft in RCS control mode
- Considered only spacecraft kinematics and neglected spacecraft dynamics:
 - ⇒ Assumed instantaneous turn rate changes ($t_{\text{maneuver}} \gg t_{\text{acceleration}}$)
 - ⇒ For EO thruster configuration, this introduces a position error of approximately 1 - 2 deg
- Assumed perfectly balanced spacecraft and thruster firing executions
- Assumed fixed initial time and free final time
- Assumed fixed initial and final attitude
- Constraint the problem to two turns per maneuver
- Assumed ephemeris of celestial objects are parametrized as a function of time



Elements of Cost Function



• Geometric Constraints:

$$C_{GC} = \sum_{slew=1}^2 \sum_{(i,j) \in \left\{ \begin{array}{l} \text{\#celest.} \\ \text{constr.} \end{array} \right\}} \sum_{\left\{ \begin{array}{l} \text{\#bore} \\ \text{sights} \\ \text{constraint} \\ \text{pair} \end{array} \right\}} F_1(\phi_{ij}^*(\cdot), \Phi_{ij})$$

$$\phi_{ij}^*(\cdot) = \phi_{ij}^*(\mathbf{c}_i, \dot{\mathbf{u}}_i, \mathbf{b}_j, \dot{\mathbf{u}}_{slew}, t_{slew})$$

$$= \begin{cases} \min_{t_o < t < t_f} \phi_{ij}(t) & \text{if } \exists \\ \phi_{ij}(t_f) & \text{else} \end{cases}$$

• Fuel:

$$C_{Fuel} = \sum_{slew=1}^2 F_3(\omega_{slew}, \omega_{max})$$

- C_{GC} : cost function for geometric constraints
- F_0 : weighting functions
- $\phi_{ij}(t)$: angular distance between constraint pair (i,j)
- Φ_{ij} : minimum required angular distance for c.p. (i,j)
- \mathbf{c}_i : celestial constraints vector
- ω_i : rotation vector of celestial constraint \mathbf{c}_i
- \mathbf{b}_i : spacecraft boresight
- ω_{slew} : spacecraft rotation vector
- t_{slew} : rotation duration
- T_{ij_max} : maximum allowable constraint violation time for c.p. (i,j)
- ω_{max} : maximum allowable turn rate
- T_{max} : maximum allowable maneuver time

• Timed Constraints:

$$C_{TC} = \sum_{slew=1}^2 \sum_{(i,j) \in \left\{ \begin{array}{l} \text{\#celest.} \\ \text{constr.} \end{array} \right\}} \sum_{\left\{ \begin{array}{l} \text{\#bore} \\ \text{sights} \\ \text{constraint} \\ \text{pair} \end{array} \right\}} F_2(T_{ij}(\cdot), T_{ij_max})$$

$$T_{ij}(\cdot) = T_{ij}(\mathbf{c}_i, \dot{\mathbf{u}}_i, \mathbf{b}_j, \dot{\mathbf{u}}_{slew}, t_{slew}, \Phi_{ij})$$

$$= \begin{cases} \text{time interval } \Delta t \text{ for which } \phi_{ij}(t) < \Phi_{ij} & \text{if } \exists \\ 0 & \text{else} \end{cases}$$

• Total Maneuver Time:

$$C_{MT} = F_4\left(\sum_{slew=1}^2 t_{slew}, T_{max}\right)$$

• Total Cost:

$$\text{Cost} = C_{GC} + C_{TC} + C_{Fuel} + C_{MT}$$

- ⇒ Time-fixed case: $\phi_{ij}^*(\cdot)$ and $T_{ij}(\cdot)$ calculated in **closed-form solution**
- ⇒ Time-varying case: $\phi_{ij}(t)$ parametrized as a function of time (t); $\phi_{ij}^*(\cdot)$ and $T_{ij}(t)$ (*) calculated by **iterative search**.

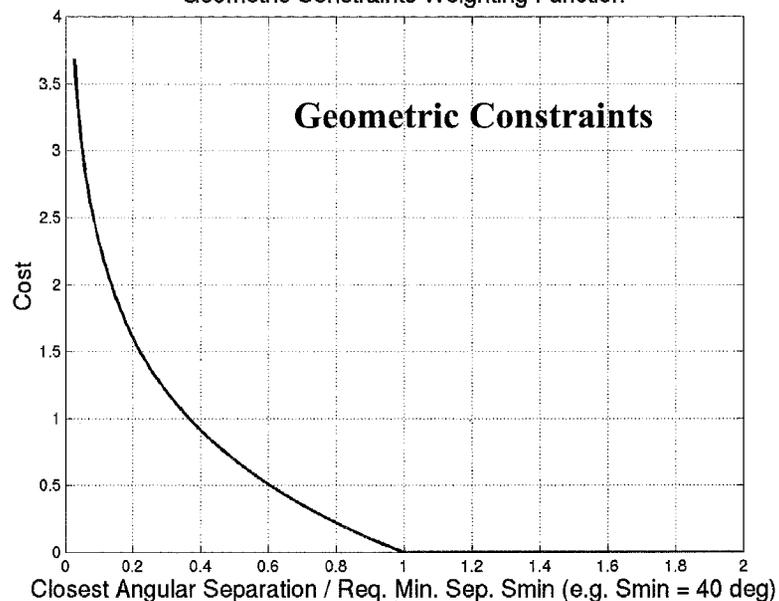
⇒ (*) not implemented



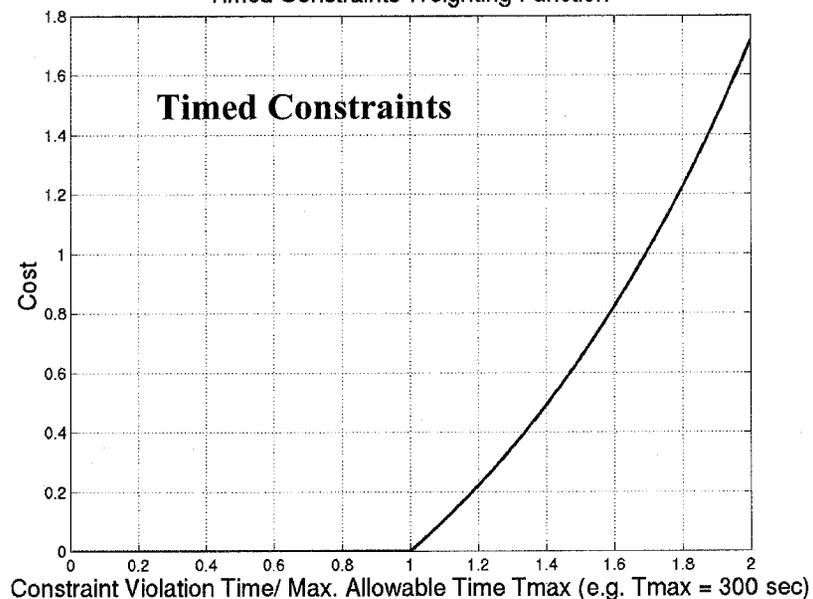
Weighting Functions



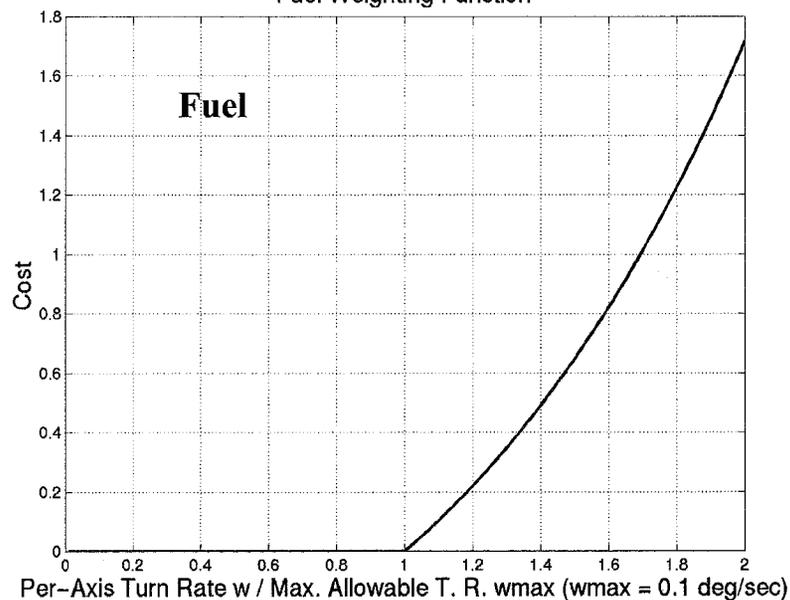
Geometric Constraints Weighting Function



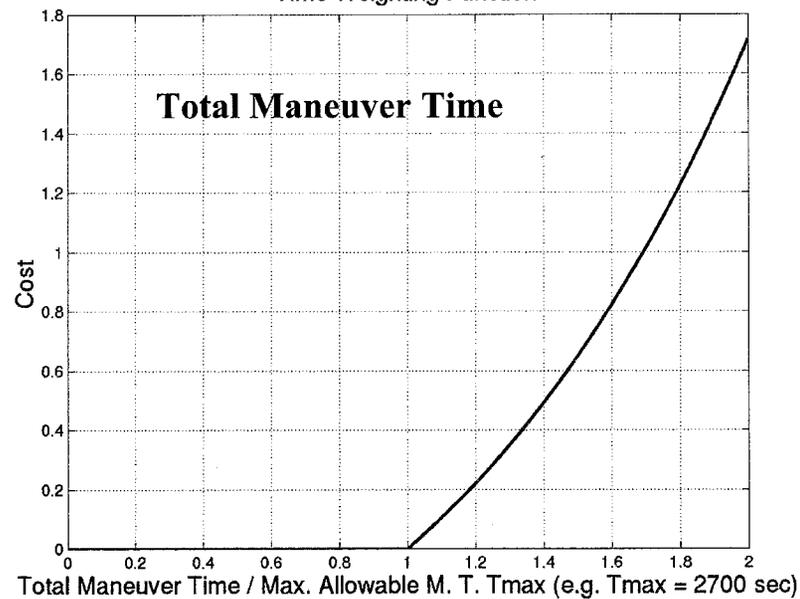
Timed Constraints Weighting Function



Fuel Weighting Function



Time Weighting Function

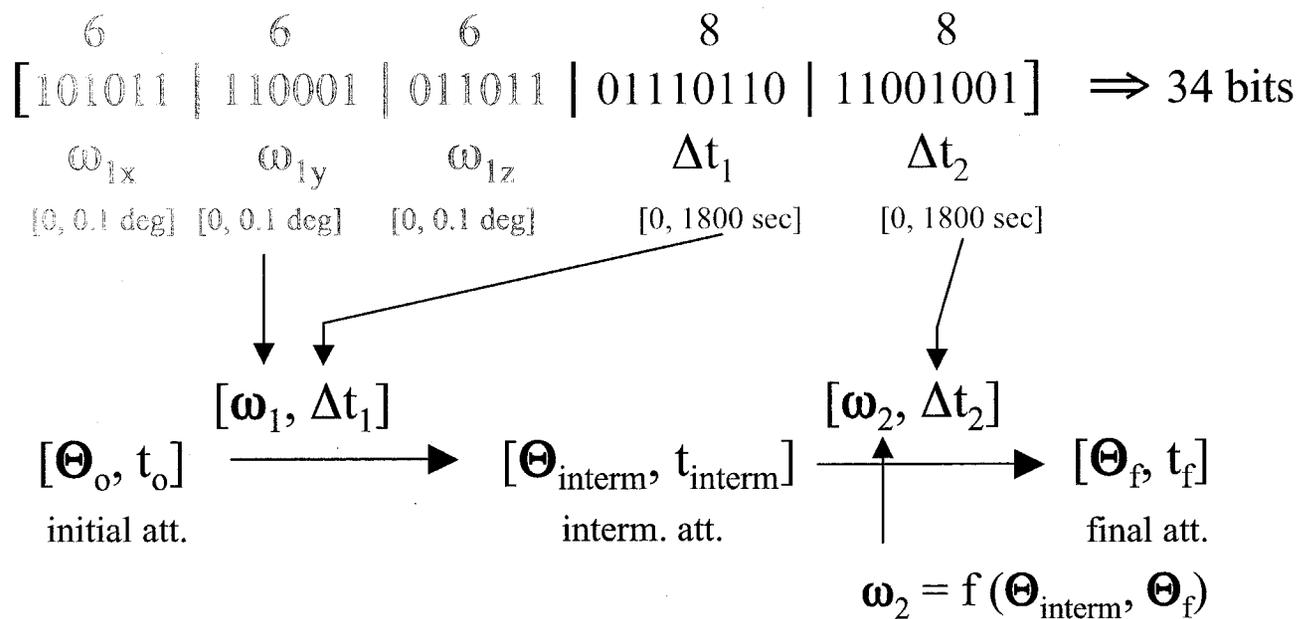




Encoding



- For this presentation:
 - Two-slew turn: $[\omega_1, t_1], [\omega_2, t_2]$
 - Fixed initial time: $t_o = 0$
 - Free final time: $t_f = t_1 + t_2$
 - Fixed initial and final attitude: Θ_o, Θ_f
- Encoded as single-level binary string/chromosome using Gray Coding:





Outline of the Basic Genetic Algorithm



1. Population: Generation n

```

0110101110110011011101
0110101001010010101010
0011111010110101010101
1101010110100101010101
1111100010101010111101
0010101011110100010101
0111101110111010111111
⋮

```

2. Evaluation of Fitness

```

2.0
0.83
1.12
1.74
0.21
0.56
0
⋮

```

3. Stopping Criteria

Stopping
Criteria
Satisfied ?

Yes

6. Stop

No

4.4. Accept New Population: Generation n + 1

```

0110101110110011011101
0110100110100101010101
1101010110110011111101
⋮
⋮

```

5. Go To Step 2.

```

2.0
⋮
⋮

```

4.1 Selection

P_{select}

```

[0110101110110011011101] [2.0]
[1101010110100101010101] [1.74]

```

4.2 Crossover

P_{cross}

```

[01101011101 | 00101010101]
[11010101101 | 10011011101]

```

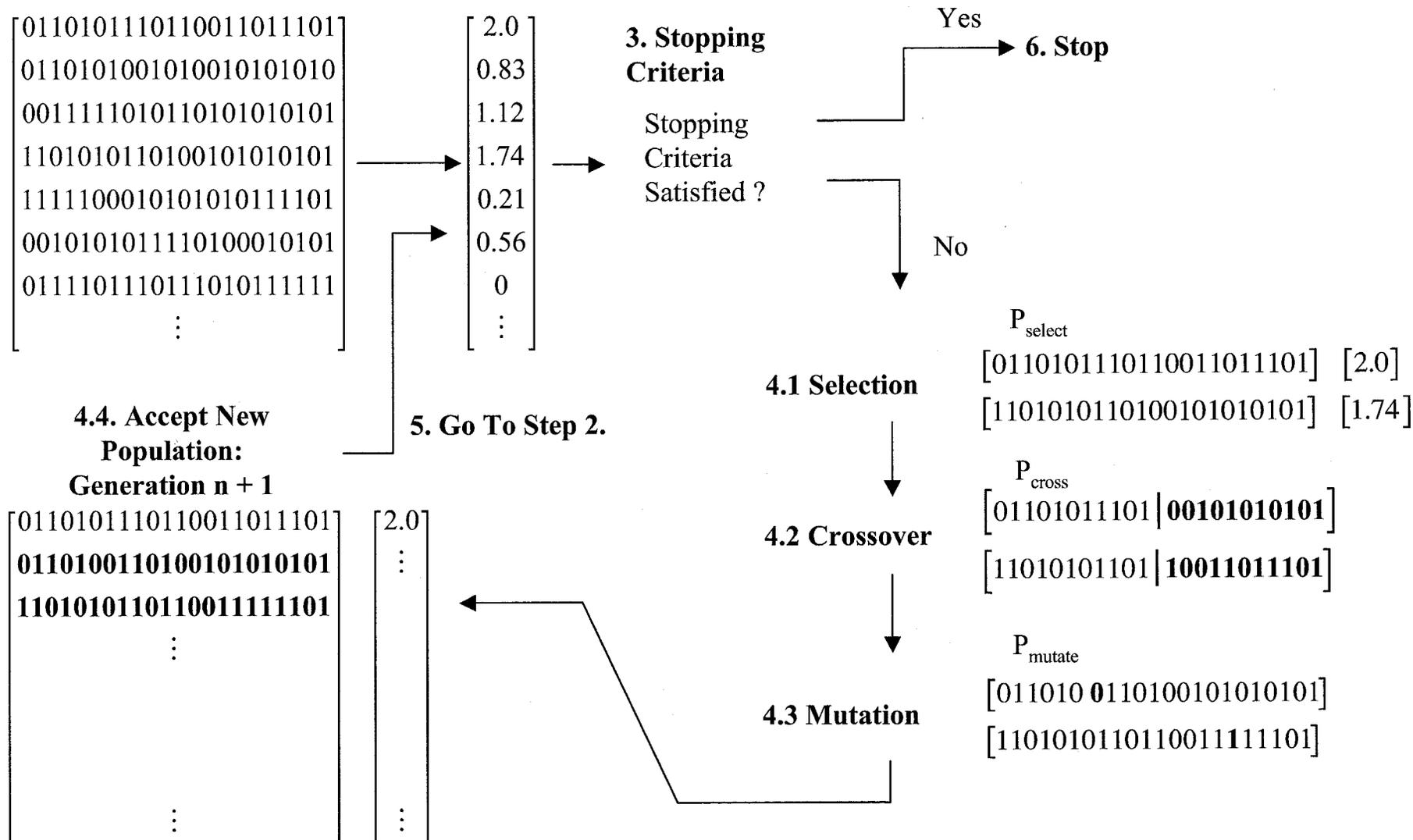
4.3 Mutation

P_{mutate}

```

[011010 0110100101010101]
[1101010110110011111101]

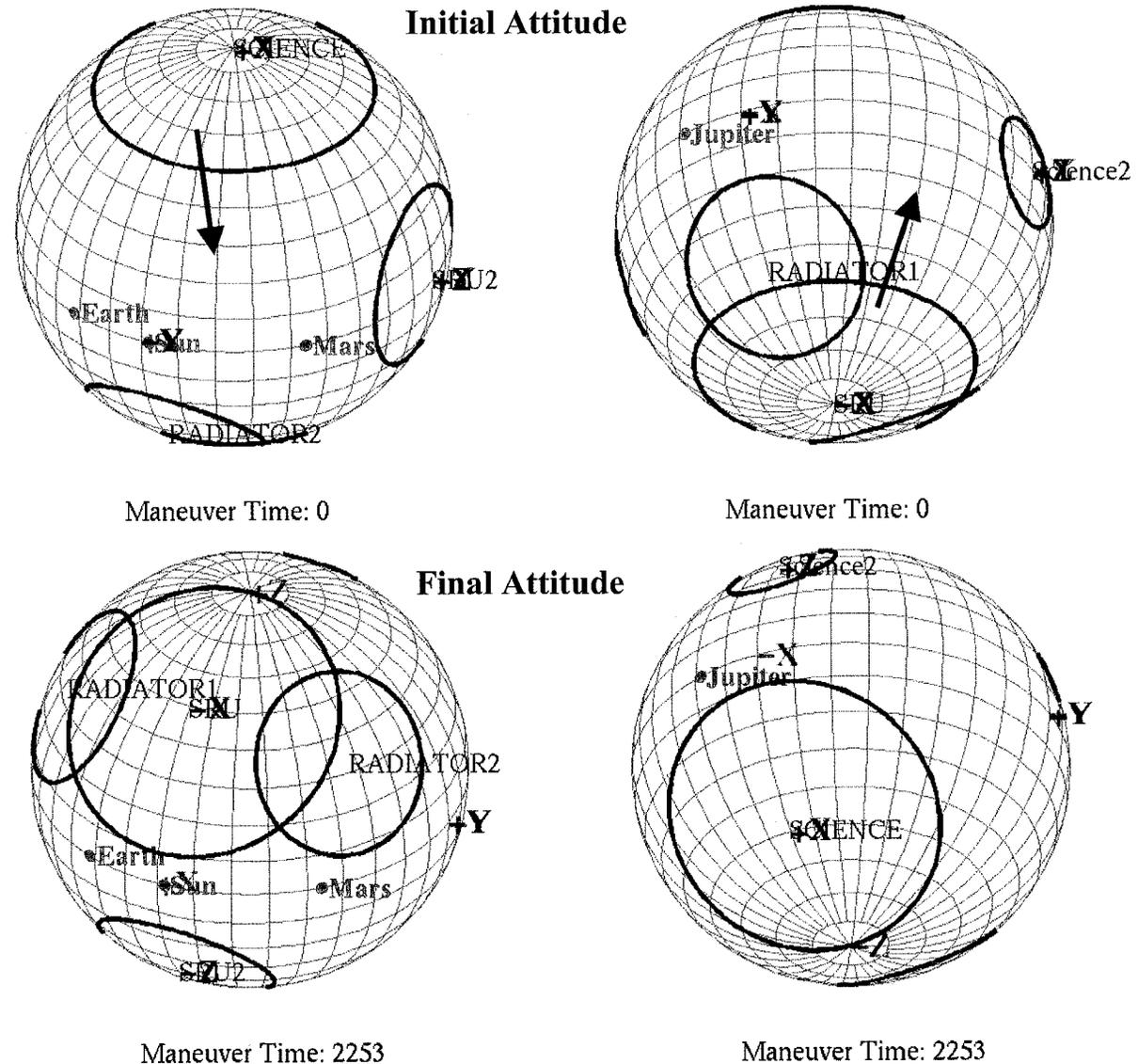
```





Example I: EO During Cruise

- Europa Orbiter during cruise (2004/06/01)
⇒ Celestial objects time-fixed
- Fixed initial and final attitude
- Fixed initial time and free final time
- Protected boresights:
 - SRU: FOV 40 deg
 - Science: FOV 40 deg
 - Radiator1: FOV 25 deg
 - Radiator 2: FOV 25 deg
 - SRU2: FOV 25 deg
 - Science2: FOV 15 deg
- Two slew maneuvers
- Rates < 0.1 deg/s per axis





Example I: EO During Cruise

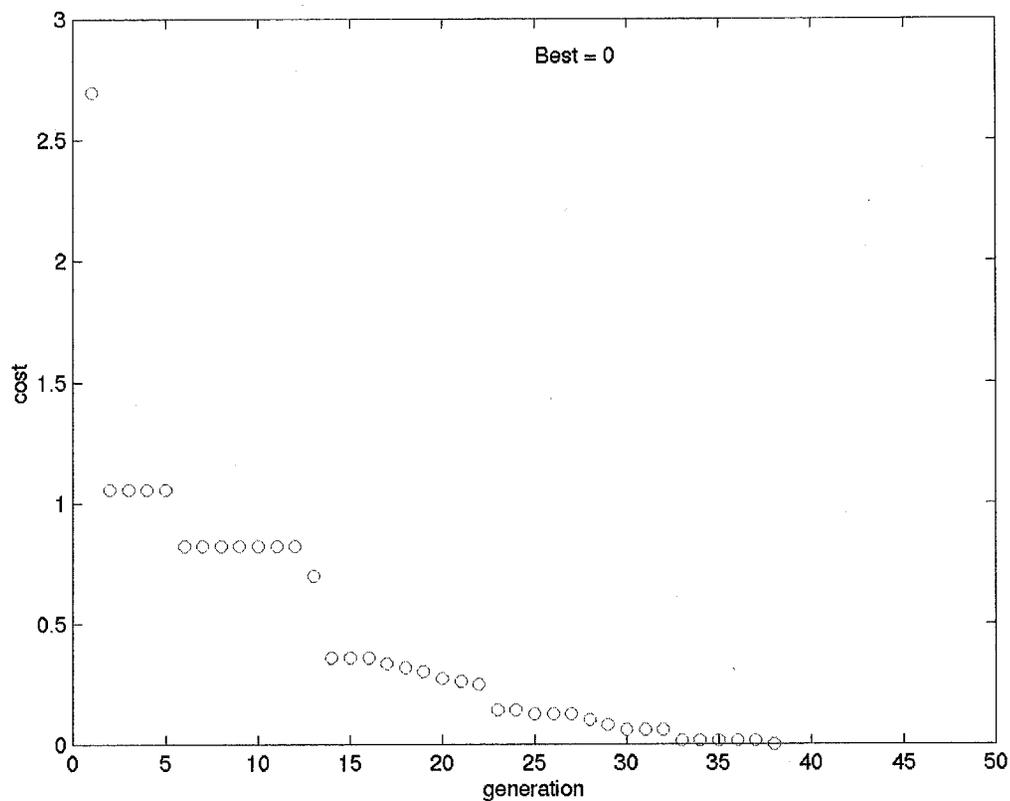
- GA Settings:

- # of chromosomes: 30
- max. # of generations: 50
- chromosome length: $L = 34$ bit
- Generation Gap = 0.9
- $P_{\text{cross}} = 0.7$
- $P_{\text{mut}} = 0.7/L$
- Stopping criteria:
cost function $< 8 \times 10^{-5}$

- Execution Time:

227 sec

Cost Function vs. Generation





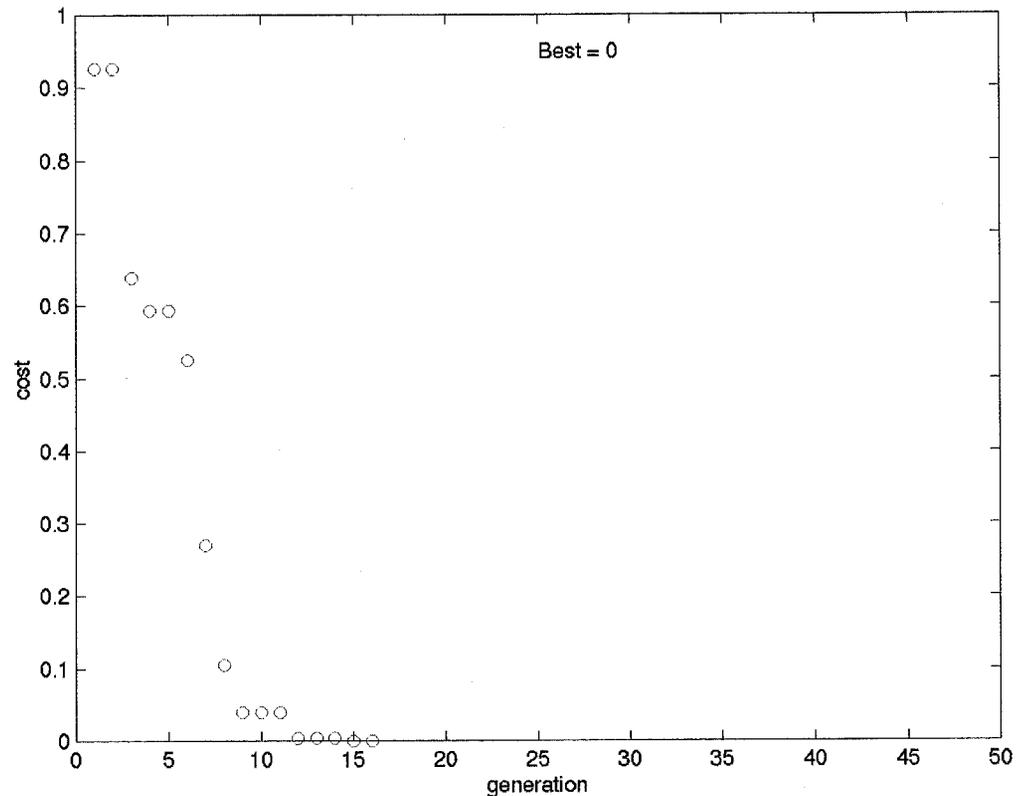
Example II: EO in Europa Orbit (EO²)

- GA Settings:

- # of chromosomes: 40
- max. # of generations: 50
- chromosome length: $L = 34$ bit
- Generation Gap = 0.9
- $P_{\text{cross}} = 0.7$
- $P_{\text{mut}} = 0.7/L$
- Stopping criteria:
cost function $< 8 \cdot 10^{-5}$

- Execution Time:

230 sec.





Summary and Conclusions



- Even a relatively simple GA based attitude planner provided acceptable solutions for a number of difficult cases
 - Computation times obtained were on the order of minutes for non-optimized code (.m files); (faster performance expected when optimized)
- ⇒ An On-board autonomous attitude planner is definitely feasible, provided that we
- trade computational tractability with optimality (e.g. through simplifications and customization)
 - abandon the notion of ‘completeness’, but instead get comfortable with the notion of ‘randomness’ (e.g. by using extensive simulations to gain confidence)
- ⇒ An attitude planner in conjunction with a Cassini/DS-1 type constraint monitor greatly increases safe, efficient and autonomous attitude maneuver planning capability



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