CS4811 Artificial Intelligence

Genetic Algorithms & Differential Evolution Nyew Hui Meen February 10, 2014

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What is a Genetic Algorithm?

A genetic algorithm (GA) is an adaptive heuristic search algorithm based on evolutionary ideas of natural selection.

When to use Genetic Algorithms?

- Search space is large, complex and difficult to understand.
- Optimization problems where the solution need not be *globally optimal*.

Elements of Genetic Algorithms

- Given a function $f(x)|_0 \le x \le 10$, the goal is to find an x value that maximizes f(x).
- In GA's terms, f is called the *fitness function*, a candidate solution x is called a *chromosome* and the f(x) value is called the *chromosome fitness*.
- A collection of chromosomes is called a *population*.

Genetic Algorithm Process

- 1. Create a population of *n* chromosomes.
- 2. Repeat the following steps until *n* offspring have been created
 - **1. Select** two parent chromosomes.
 - 2. Produce two offspring from the parent chromosome by **crossover**.
 - 3. Mutate the offspring.
 - 4. Place the offspring in the new population.
- 3. Repeat step 2 until termination conditions are met.

Create Population

Example population of size 3

Chromosome label	Chromosome stríng	Fítness
<i>A</i>	110	1
${\cal B}$	001	2
С	101	3

The Selection Operation

- Random selection
- Fitness-proportionate selection

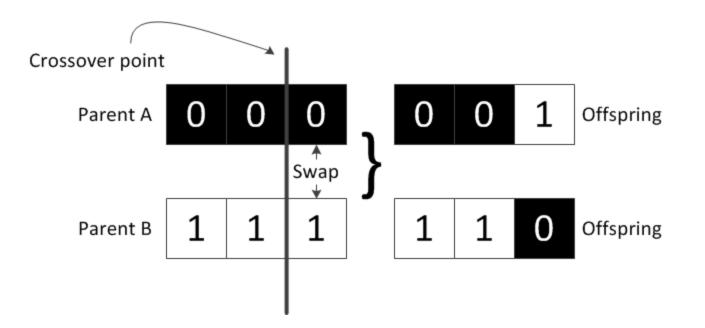
Probability a chromosome selected is equal to its fitness divided by the total fitness in the population.

Comparison of Selection Method

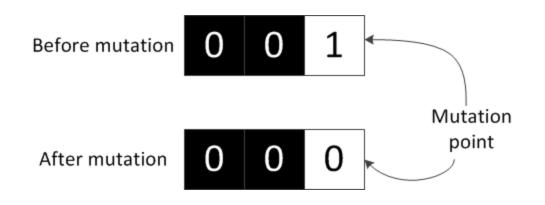
Chromosome	Chromosome			Fítness-
label	string	Fítness	Random	proportionate
A	110	1	33%	17%
B	001	2	33%	33%
С	101	3	33%	50%

The Crossover Operation

Single-point Crossover



The Mutation Operation



Differential Evolution Process

- 1. Create a population of *n* chromosomes.
- 2. Repeat the following steps until *n* offspring have been created for every chromosome *x* in the population.
 - 1. Select two three parent chromosomes, **a**, **b** and **c**.
 - 2. Produce two **one** offspring from parent chromosomes by crossover **transformation operation**.
 - 3. Mutate the offspring.
 - 4. Place the offspring in the new population, if the offspring's fitness is better than x's fitness.
- 3. Repeat step 2 until termination conditions are met.

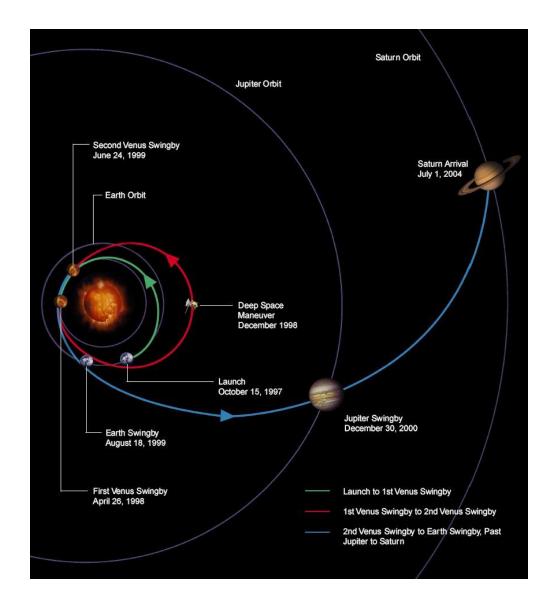
Transformation

- 1. For every parameter x_i in chromosome x:
 - 1. Pick a random number *r*.
 - 2. If r < transformation probability p: Compute new offspring y parameter y_i as follows: $y_i = a_i + F(b_i - c_i)$
 - 3. If $y \ge$ transformation probability p: Compute new offspring y parameter y_i as follows: $y_i = x_i$
- \clubsuit *F* is differential weight

Transformation Example

- Chromosomes
 - -x = [1,4]
 - -a = [2,3]
 - b = [4,6]
 - c = [9,4]
- Transformation variables:
 - -F = 1
 - p = 0.5
- Let first r = 0.4. $y_1 = a_1 + F(b_1 c_1) = 2 + (4 9) = -3$
- Let second r = 0.7. $y_2 = x_2 = 4$
- Thus offspring y = [-3,4]

Cassini Mission

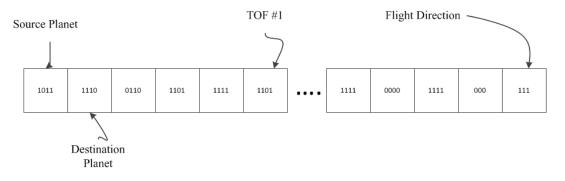


Variable-length Chromosome

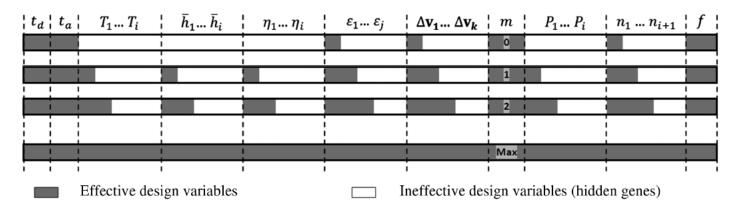
- Cassini Mission's fitness function is complex and its chromosomes have variable length.
- This creates difficulty for single-point crossover operation.

Cassini Mission's Chromosome

Fixed length Chromosome



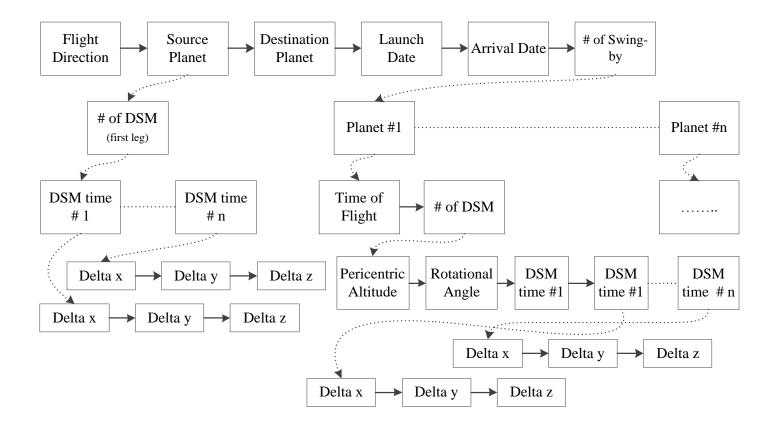
Fixed length Chromosome with Hidden Genes



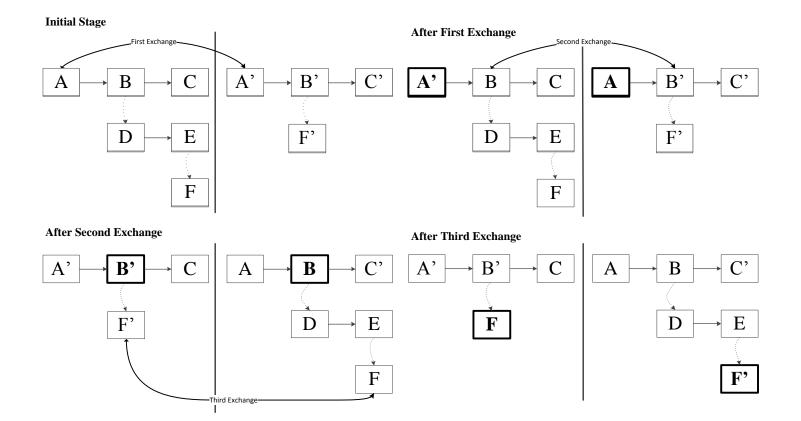
Structured Chromosome

- Describe parameters with *parameter existential dependency relationship*.
- Chromosomes grow and shrink during crossover and mutation operations.

Cassini Mission Chromosome



Structured Chromosome Crossover Operation



Experiment Setup for Cassini Mission

- Crossover probability = 0.1
- Mutation probability = 0.1

Parameter	upper bound	Lower bound
Source Planet	з (Earth)	3 (Earth)
Destination Planet	6 (Saturn)	6(Saturn)
Number of Swing-	4	3
by		
Planet	2	5
Launch year	1997	1997
Launch month	11	11
Launch day	31	1
Arríval year	2007	2007
Arrival month	6	1
Arríval day	30	1
Time of flight	1000	40
Number of DSM	0	0
Flight Direction	1	0

Experiment Process

- We run SCGA and SCDE 200 times and store each run's best solution.
- Then the solutions are optimized by running it through the MATLAB local optimization toolbox.
- For each set of solutions, we compute their success rate of producing the target cost and the success rate of producing the target planet sequence.

Success rate calculations

```
tolerance \leftarrow 0.1
best_cost \leftarrow 12
success_count \leftarrow 0
i \leftarrow 1
while i \leq 200 do
  if cost(i) \leq best_cost then do
    success_count \leftarrow success_count + 1
    best_cost \leftarrow cost(i) + tolerance
  success_rate(i) \leftarrow success_count/i
  i \leftarrow i + 1
```

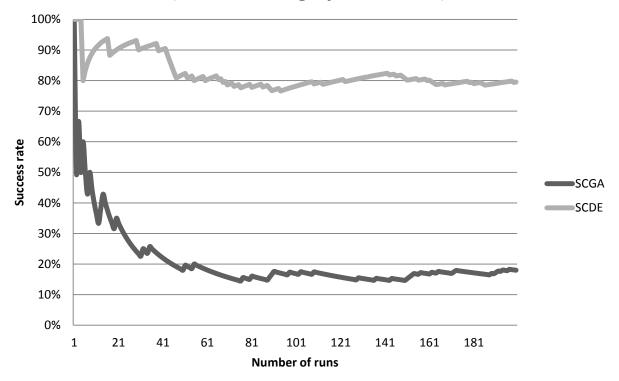
```
best_sequence ← 235
success_count ← 0
i ← 1
while i ≤ 200 do
    if cost(i) ≤ best_sequence then do
        success_count ← success_count +
1
success_rate(i) ← success_count/i
    i ← i + 1
```

Experimental Results (1)

Success rate of producing the target cost (before running optimization) 100% 90% 80% 70% 60% Success rate 50% SCGA 40% SCDE 30% 20% 10% 0% 21 41 1 61 81 101 121 141 161 181 Number of runs

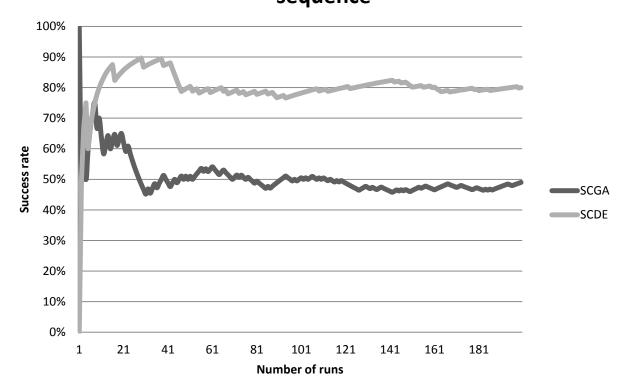
Experimental Results (2)

Success rate of producing the target cost (after running optimization)



Experimental Results (3)

Success rate of producing the target planets sequence



References

- A. E. Eiben & J. E. Smith, Introduction to Evolutionary Computing, Springer, 2008
- O. Abdelkhalik and A. Gad, Dynamic-Size Multi-Population Genetic Optimization for Multi-Gravity-Assist Trajectories, AIAA Journal of guidance, control, and dynamics. Accepted, July 2011, doi: 10.2514/1.54330
- A. Gad, O. Abdelkhalik, Hidden Genes Genetic Algorithm for Multi-Gravity-Assist Trajectories Optimization, AIAA Journal of Spacecraft and Rockets, AIAA, Vol. 48, No 4, pp 629-641, July-August 2011. doi: 10.2514/1.52642