MECE 4510: Evolutionary Computation and Design

Project - Phase B

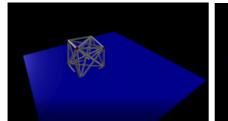
Jerry Zhang | UNI: jz2966 | Grace Hours Remaining: 62 + 4 = 66 Zhengyang Du | UNI: zd2219 | Grace Hours Remaining: 57 + 4 = 61

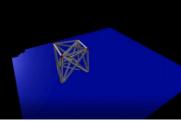
Instructor: Professor Hod Lipson Date Submitted: 11/30/2018

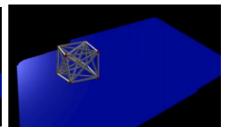
RESULTS

Fastest Robot:

https://www.youtube.com/watch?v=ffnTuuv-64s&t=3s

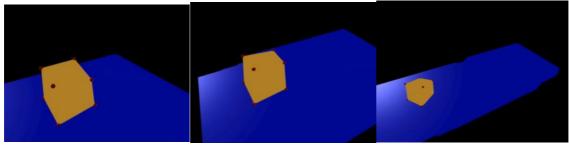






Fastest Robot w/ shaded faces:

 $\underline{https://www.youtube.com/watch?v=}ffnTuuv-64s\&t=26s$

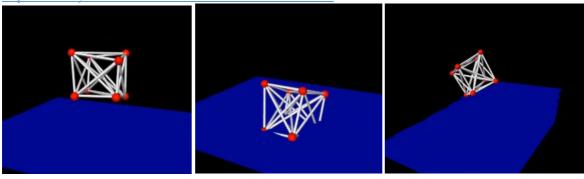


Speed:1.4 m/s

Fitness: 2.83 m (when simulated for 2 seconds)

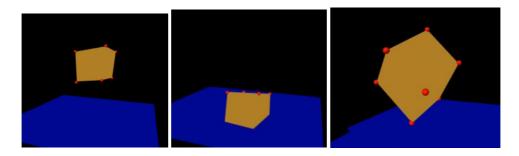
Fastest Robot Bouncing:

https://www.youtube.com/watch?v=ffnTuuv-64s&t=48s



Fastest Robot Bouncing w/ Shaded Faces:

 $\underline{https://www.youtube.com/watch?v=} fnTuuv-64s\&t=71s$

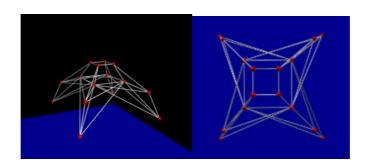


Speed: 2.35 m/s

Fitness: 4.70 m (when simulated for 2 seconds)

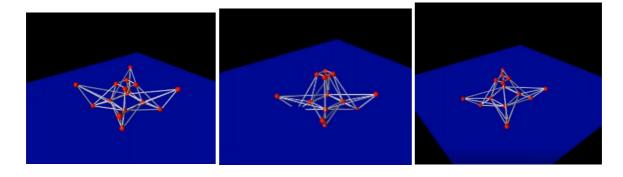
Innovative Robot

Design:



Evolution:

https://www.youtube.com/watch?v=ffnTuuv-64s&t=90s



Speed: 1.06 m/s

Fitness: 2.11 m (when simulated for 2 seconds)

METHODS

Actuation Methodology

A cube robot with 28 springs and 8 mass nodes was evolved. Each lengths between each mass, all 28, were evolved to actuate based on an initially random and then evolved sinusoidal value. In order to evolve the cube, a locomotion pattern was evolved between each mass. Rest length L_0 of each spring is defined as:

$$L_0 = a + b * \sin(wt + c)$$

Where a is the original rest length, and b is a random value between [-0.2, 0.2] and c is a random value between $[-\pi, \pi]$.

Based on python's limitations, the spring evaluations per second is as follows:

Number of Spring Evaluations per second: 16632 springs/second.

Performance (Maximum Diameter per Cycle):

The velocity of our cube moving was 2.8m / 2s which would give us 1.4 m/s. The diameter for our cube was 1.73 meters. Therefore, by dividing 1.4m/s by 1.73m, 80.92%/s was obtained which demonstrated that our robot walk for a distance per second that was almost 81 percent of the diameter.

Evolutionary Process and Analysis

Below are the simulation and robot parameters used for the cube robot Simulation Parameters:

Total Evolution Time	dT	Gravity	Spring Constant Floor
2 sec	.001 sec	$9.81 \ m/s^2$	N/m

Robot Parameters:

# Masses	# Springs	Total Mass	Spring Constant
8	28	0.8 kg	N/m

For the evolutionary process, we wanted to evolve a robot that would move as far and fast as possible. Thus, fitness was defined as the magnitude of the initial origin and the final distance its center of mass has moved. A total population of 10 cubes were evolved due to the computational limitation of vpython (a simulation library). The mutation rate was set to 20%, and when achieved, would randomly switch the locomotion parameters b, c of two springs in the children of the population. Cross over was achieved by first selecting a set of 8 locomotion parameters of b, c, and k randomly from the 28 total possible locomotion ordered pairs. Note that 8 individual locomotion parameters were not randomly selected from the 28; rather, the 8 were locomotion parameters from 1 or two mass nodes. This crossover strategy and value was selected to increase linkage and preserve dominant genes.

However, there were still some limitations about the crossover and mutation mechanism. Since there were lack of new individual being added in to the population, the crossover and mutation occurred only between the initially generated parameters. The strategy still managed to grow and give better generations, but the diversity within the population would became limited once more generations were evaluated. Increasing the population size would improve this a little bit but a better way to improve it might be introducing new random parameters when mutation occurred so that new genes order can be explored that could potentially increase the performance of the generations and better fitness.

Innovative Robot Evolutionary Process and Analysis

Below are the parameters for the innovative robot:

Alternative Robot Parameters:

# Masses	# Springs	Total Mass	Spring Constant
16	120	0.8 kg	N/m

For the alternative robot, we wanted to create a spider with two joints per leg. To simulate the robot, we created two-layers of masses that initially lie on similar respective planes, as well as springs that connect them with the respective masses to control the degrees of freedom in which they can move. Unfortunately, due to the way our code is written, we are unable to compartmentalize individual locomotion in individual springs. Everything in our code operates as a reaction to a mass, that subsequently affects every other mass. This method was optimal for our cube robot, but less optimal for our alternative design. We'd optimally only want to actuate 32 new springs, but we are actually actuating 120 springs with our design. Theoretically, the evolutionary algorithm should still be able to effectively evolve our robot to move as far as possible, but it would do so in a much less efficient way than if we were to be able to control locomotion in individual springs. A ground up rework of our code is necessary if we were to continue with this spider design.

PERFORMANCE PLOTS

Learning Curve:

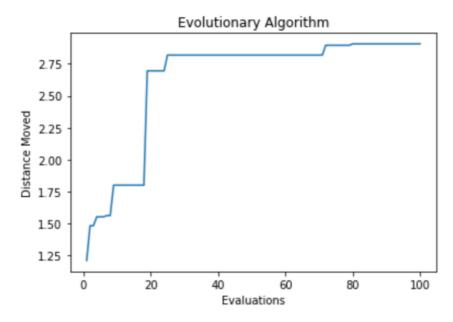


Figure 4: Learning curve for walking robot with 100 generations (2000 evaluations)

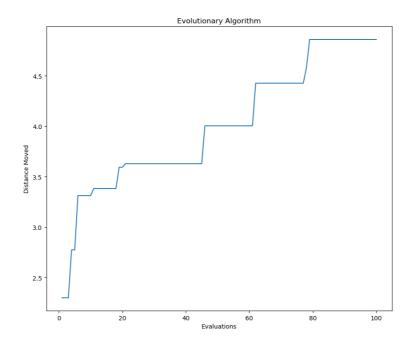


Figure 5: Learning curve for walking robot with bouncing with 100 generations (2000 evlatuions)

Dot Chart:

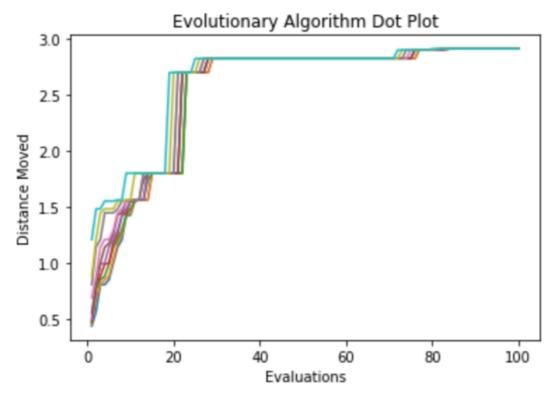


Figure 5: Dot chart for walking cubes

APPENDIX

Evolutionary Algorithm for Walking Cube Evolution

```
import veythen as verification import itertools import random import numpy as np
best_dis = []
mutation_rate
```

```
pa1 = []

for i in range(10):
    pa = []
```

```
Lorate[0][3] = Lo[0][3] + pal[h][2][0] * sin(w * t + pal[h][2][1])

Lorate[3][0] = Lo[3][0] + pal[h][2][0] * sin(w * t + pal[h][2][1])

Lorate[0][4] = Lo[0][4] + pal[h][3][0] * sin(w * t + pal[h][3][1])
```

```
sorted_dis.append(total_dis[dis_index[i]])
sorted_pal.append(pal[dis_index[i]])
```

Evolutionary Algorithm for Walking Cube SIMULATED

```
import vpython as vp
import itertools
# vp.display(width=100, height=100)
floor = vp.box(pos=vp.vector(0, 0, 0), length=5, height=0.001, width=5, color=vp.color.blue)
ballname = ['b1', 'b2', 'b3', 'b4', 'b5', 'b6', 'b7', 'b8']
ballvectors = [vp.vector(0, 0, 0), vp.vector(0, 1, 0), vp.vector(0, 0, 1), vp.vector(1, 0, 0),
```

Innovative Robot Evolution

```
import vpython as vp
import itertools
import numpy as np
from math import *
import random
import matplotlib.pyplot as plt

scene = vp.canvas()  # title = 'Box', width = 600, height = 400, center = vp.vector(0,0,0))

floor = vp.box(pos=vp.vector(0, -1.3, 0), length=10, height=0.01, width=10, color=vp.color.blue)

def getCOM(v):
    COM = (v[0].pos + v[1].pos + v[2].pos + v[3].pos + v[4].pos + v[5].pos + v[6].pos + v[7].pos + v[8].pos + v[9].pos + v[11].pos + v[12].pos + v[13].pos + v[14].pos + v[15].pos) / 16
    return COM
```

```
for j in range(len(index)):
    M[index[j]] = exchangen[j]
    N[index[j]] = exchangem[j]
good_dis = []
best_dis = []
dt = 0.001
pa1 = []
for i in range(10):
```

```
ballvectors[i + 2]],
```

```
plt.ylabel('Distance Moved')
plt.title('Evolutionary Algorithm')
plt.show()

plt.plot(evals, dots)
plt.xlabel('Evaluations')
plt.ylabel('Distance Moved')
plt.title('Evolutionary Algorithm Dot Plot')
plt.show()
```

Innovative Robot SIMULATED

```
[ballvectors[4], ballvectors[6]], [ballvectors[7], ballvectors[5]], [ballvectors[7], ballvectors[6]]]
```

```
ballname2 = ['b9', 'b10', 'b11', 'b12']
ballname3 = ['b13', 'b14', 'b15', 'b16']
```

```
vz = ballnameC[i].velocity.z / v_xz
```