Projeto Final

Machine Learning Engineer Nanodegree

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Detecção de Falhas em Circuitos Elétricos

Definição

***Visão Geral do Projeto***

O desenvolvimento de estratégias de teste para detectar e diagnosticar falhas em  
circuitos analógicos e de sinais mistos é uma tarefa desafiadora que tem encorajado uma  
boa quantidade de pesquisas, devido ao aumento do número de aplicações destes circuitos  
e ao alto custo dos testes. Muitas áreas, tais como, telecomunicações, multimídia e  
aplicações biomédicas, precisam de bom desempenho em aplicações de alta frequência,  
baixo ruído e baixa potência, o que só se pode ser alcançado através do uso de circuitos  
integrados analógicos e de sinais mistos. Assim, uma estratégia para detectar e diagnosticar  
falhas nesse tipo de circuitos é muito importante (Albustani, 2004). No passado, um circuito  
integrado era apenas um componente em um sistema, mas hoje o circuito integrado em si é  
o sistema inteiro (SoC - system on a chip). Com esse nível de integração, problemas difíceis  
de teste e projeto foram gerados. Dentre os vários fatores que aumentam as dificuldades,  
pode-se citar: a falta de bons modelos de falhas, falta de um padrão de projeto com vistas à  
facilidade de testes e o aumento da importância das falhas relacionadas ao tempo de vida  
dos componentes (Claasen, 2003). Assim, a estratégia de testes para detecção e diagnóstico  
de falhas ainda é severamente dependente da perícia e da experiência que os engenheiros  
têm sobre as características do circuito. Então a detecção e a identificação de falhas ainda  
são um processo interativo e que consome bastante tempo. Um estudo na área de detecção  
e diagnóstico (Fenton, 2001) mostrou que, nas últimas décadas, uma boa quantidade de  
pesquisa em diagnósticos de falhas foi concentrada em desenvolver ferramentas que  
facilitassem as tarefas de diagnóstico. Embora progressos importantes tenham sido  
alcançados, essas novas tecnologias não têm sido largamente aceitas. Isso deve motivar os  
pesquisadores a investigar outros paradigmas e desenvolver novas estratégias para  
diagnósticos de falhas.

O uso de técnicas de inteligência computacional para diagnóstico é normalmente  
baseado na construção de modelos ou no uso de classificadores, cujo sucesso e desempenho  
depende da qualidade do modelo obtido, o que, no caso de um sistema complexo, pode ser  
difícil de obter. Os classificadores multiclasse procuram por comportamentos específicos de  
falhas e se mostram vulneráveis a superposição de padrões de falha ou a padrões de falha  
que não foram apresentados durante a fase de treinamento. Classificadores de classe única  
podem ser treinados para resolver problemas de classificação binária onde apenas uma das  
classes é bem conhecida (Tax, 2001). Estes podem ser organizados na forma de conjunto  
(ensemble) de classificadores e com isso reduzir alguns dos problemas encontrados com  
classificadores multiclasse citados anteriormente. Esta proposta de projeto apresenta o  
esboço do desenvolvimento de um sistema de detecção de falhas em circuitos lineares e  
invariantes no tempo, onde os resultados de diferentes métodos serão comparados para a  
determinação do melhor tipo de classificador

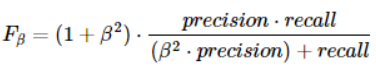
***Descrição do Problema***

O termo falha é definido como uma condição anormal ou defeito (ISO/CD  
10303), em um componente, equipamento ou sistema que pode conduzir ao mau  
funcionamento, isto é, uma diminuição parcial ou total na capacidade de desempenhar  
a função desejada por certo intervalo de tempo.

Em circuitos analógicos, as falhas podem ser classificadas usando diferentes  
critérios. O tipo de falha abordada neste projeto é aquela que se dá em função do  
desvio do parâmetro de um sistema (ou componente do sistema) no tempo, designada  
falha paramétrica, forçando-o a assumir um valor que está fora de sua faixa nominal. Quando existe um desvio repentino muito grande do valor do parâmetro desejado,  
este é chamado de falha catastrófica. Este tipo de falha está associado à mudança da  
estrutura do sistema. Alguns exemplos de falhas catastróficas em circuitos elétricos  
seriam o circuito aberto e o curto-circuito (DUHAMEL E RAULT, 1979).

***Métricas***

Como a alteração causadora da falha no circuito é previamente determinada, é  
possível usar um “gabarito” para qualificar e quantificar a precisão do modelo de  
predição. Desta forma é possível empregar as métricas do próprio scikit-learn, como o  
fbeta\_score.



O F-beta score é um método de avaliação de precisão que representa o desempenho do modelo de predição com maior precisão por considerar não apenas os acertos e a quantidade total de elementos, mas também os falsos positivos e os falsos negativos.

Análise

***Exploração e Visualização de Dados***

Os dados de simulação ordinários do LTSpiceIV são salvos em um arquivo “.raw” que contém informações de todas as grandezas do circuito para todos os passos de simulação, bem como dos passos de tempo referente aos passos de simulação, um cabeçalho com título do arquivo de simulação e outros metadados, e até alguns dados criptografados. Segue um trecho do arquivo .raw referente ao circuito Nonlinear Rectfier:

Title: \* <caminho do sistema>\Nonlinear Rectfier + 4bit PRBS [FALHA] - 300 - 0.2s.asc

Date: Sat Oct 06 16:15:11 2018

Plotname: Transient Analysis

Flags: real forward stepped

No. Variables: 32

No. Points: 3325566

Offset: 0.0000000000000000e+000

Command: Linear Technology Corporation LTspice IV

Variables:

0 time time

1 V(vin) voltage

2 V(n001) voltage

3 V(v1) voltage

4 V(vout) voltage

...

29 I8(A1) device\_current

30 I7(A1) device\_current

31 I6(A1) device\_current

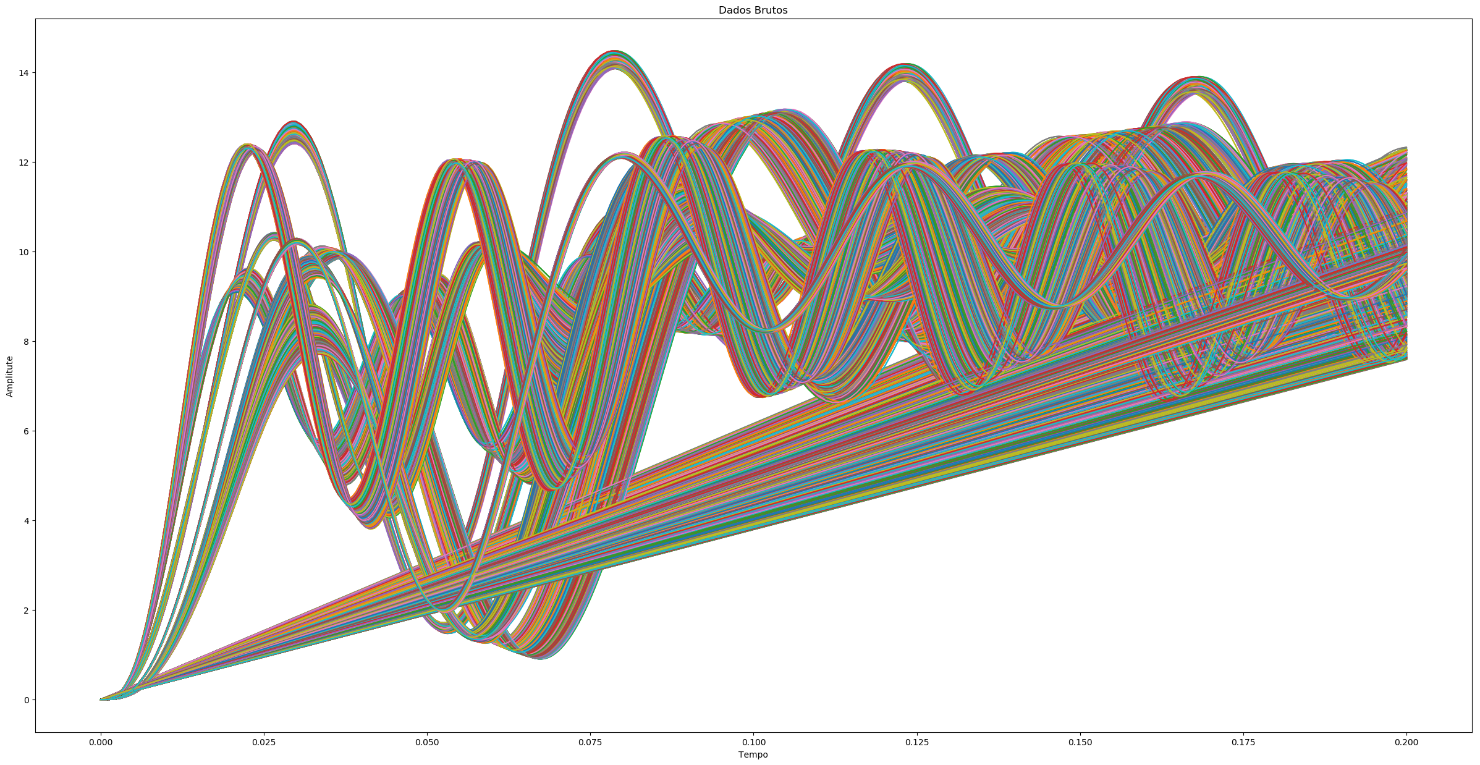
Binary:

¶‘¤¡SØKŽ›ÏKŽ› + [1352054 linhas de dados binários representados, quando possível, em hexadecimal] + D¹

O arquivo raw é bem completo e este, por exemplo, possui cerca de 429MBytes de informação. Assim seria necessário um projeto só para extrair as informações necessárias do arquivo, e então foi usado um toolchain existente para a extração dos dados. Através do "LTSpiceRaw\_Reader.py", as informações pertinentes extraídas do arquivo raw foram obtidas e salvas em um arquivo “.csv” de tamanho menor e já no formato de dataframe, que será usado ao longo do projeto:

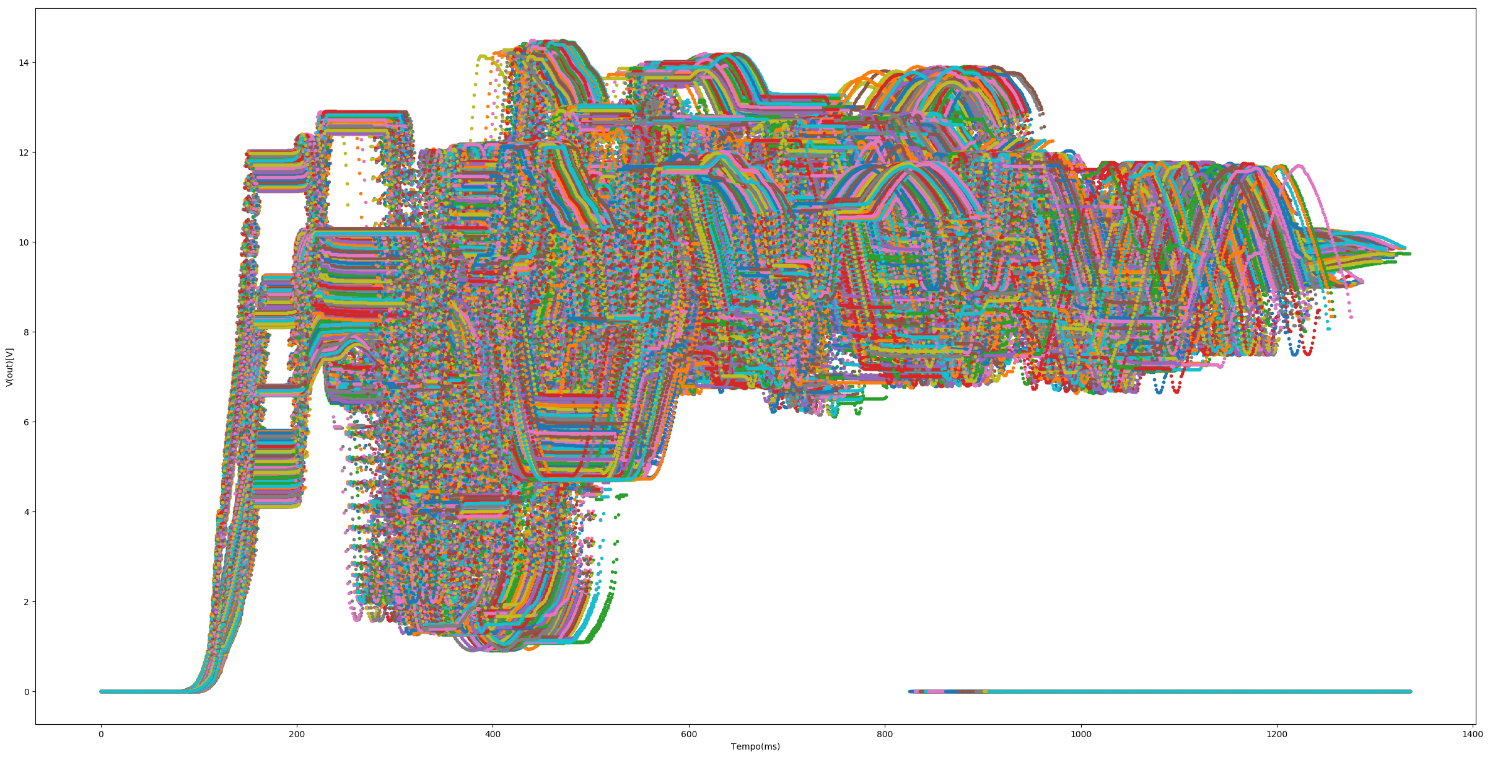
|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | 0 | 1 | 2 | ... | 3297 | 3298 | 3299 |
| 0 | -2,35E-06 | 1,77E-06 | 1,01E-06 | ... | -8,97E-08 | -2,17E-07 | -2,48E-07 |
| 16 | -2,35E-06 | 1,78E-06 | 1,01E-06 | ... | -8,37E-09 | -2,11E-06 | -2,42E-06 |
| 18 | -2,35E-06 | 1,79E-06 | 1,01E-06 | ... | 7,16E-03 | 7,16E-02 | 9,12E-03 |
| 19 | 1,20E-01 | 1,85E-06 | 1,02E-07 | ... | 5,69E-01 | 5,69E-01 | 5,75E-01 |
| 20 | 9,59E-03 | 1,36E-04 | 1,68E-01 | ... | 4,53E+00 | 4,53E+00 | 4,57E+00 |

O gráfico a seguir traz a plotagem dos dados da saída da simulação sobre os quais serão aplicados os métodos de aprendizagem:



***(Figura: Dados originais extraídos do circuito Nonlinear Rectifier)***

E os dataframe populado com estes dados possui a seguinte característica:



***(Figura: Valores de Vout de cada passo de simulação plotados individualmente)***

Através destes dados podemos observar que existem alguns valores que aparentam estar fora do comportamento padrão das demais simulações. Porém, devo ressaltar que estes são dados resultantes de simulações de falhas elétricas e, portanto, estes não devem ser tratados como outliers pois carregam informações importantes sobre o comportamento das falhas.

***Algoritmos e Técnicas***

If the robot explores the entire maze, we can use A\* algorithm to find the shortest path from the start location to the goal area. Therefore, in the first run, the robot should try exploring the maze as much as possible and expand the mapping area so that, in the second run, the robot can apply the A\* search algorithm to find the optimal path and moves. On the other hand, the robot should try reaching the goal as fast as possible in the first run as it affects the score value and if too much time is spent in the first run, it may not be able to leave enough time for the second run.

For the first run, I will use the following techniques for the robot controller to explore the maze and expand the mapping area while seeking the goal area:

• Random move

• Random move with dead-end path detection

• Counting number of visits for each location in order to expand into less visited area

• The counting logic with heuristic prediction of the distance to the goal

The random move controller will take the robot to different paths randomly. It is not most efficient way to expand the mapping area but it gives the baseline performance to compare with more advanced techniques. Also, this controller will prove that the robot movements and rotations are handling walls properly.

The dead-end path detection will prevent the robot to enter dead-ends more than once making it more efficient to expand the mapping area than the pure random controller.

The counting number of visits for each location will give the robot chances to move to less frequently visited locations. It will also make the robot moves out of loops.

The heuristic values will be used to make the robot move towards the goal area making it faster to reach the goal area.

For the second run, I will use A\* search on the mapped area from the first run in order to find the optimal path/moves to the goal.

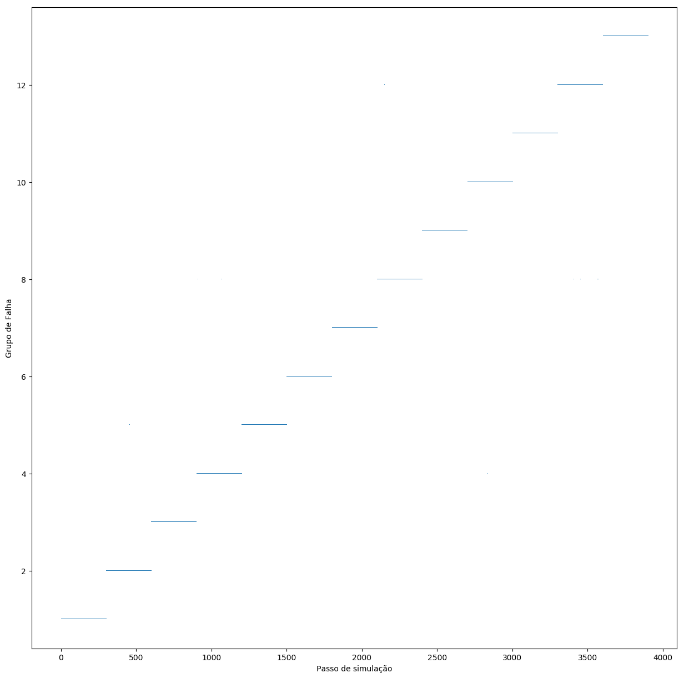
In A\* search, G values give the cost of reaching to each location in the maze from the start position. The turning left or right is given higher cost than the forward move. Heuristic values gives the distance of each location in the maze from the goal area. A\* search uses the F values which are combination of G values and Heuristic values to find the optimal path from the start location to the goal area.

As the maze structure is well defined, I will use the test maze data to test the A\* search program. I’ll provide a separate python script to run the test without using the robot tester program.

***Benchmark***

Os circuitos são simulados inicialmente em estado de funcionamento normal, e  
cada estado de falha é causado forçadamente, isto é, existe uma função no LTSpiceIV  
que causa a alteração dos parâmetros dos componentes de forma ordenada, prevista.  
Desta forma, para um dado conjunto de passos de simulação é possível prever qual foi  
o componente causador da falha, e qual o valor que levou àquela falha.  
No caso específico do circuito “Sallen Key mc + 4bitPRBS \*FALHA+” o algoritmo gerador das falhas em tempo de simulação é:

ac dec 100 10k 1meg  
.step param run 1 3300 1  
.tran 300us  
.function falhaR1(baixo,alto,mc) if((run>X)&(run<=2\*X), alto,if (run<=X,baixo,mc))  
.function falhaR2(baixo,alto,mc) if((run>3\*X)&(run<=4\*X), alto,  
if ((run<=3\*X)&(run>2\*X),baixo,mc))  
.function falhaR3(baixo,alto,mc) if((run>5\*X)&(run<=6\*X), alto,  
if ((run<=5\*X)&(run>4\*X),baixo,mc))  
.function falhaC2(curto,aberto,normal) if((run>9\*X)&(run<=10\*X),aberto,  
if((run<=9\*X)&(run>8\*X),curto,normal))  
.function falhaC1(curto,aberto,normal) if((run>7\*X)&(run<=8\*X),aberto,  
if((run<=7\*X)&(run>6\*X),curto,normal))  
.param X=300

Com o objetivo de obter um retorno visual, de avaliação humanamente imediata, do desempenho da solução, os resultados dos treinos e das classificações serão plotados. O gabarito com estes para a comparação avaliação destes resultados se assemelha a uma escada, onde os degraus são os grupos de falhas. A imagem a seguir apresenta o gabarito para o circuito Biquad Highpass Filter mc + 4bitPRBS [FALHA].

***(Figura: Gabarito gráfico do circuito Biquad Highpass Filter mc + 4bitPRBS [FALHA])***

Metodologia

***Pré-processamento de Dados***

O pré-processamento dos dados se resumiu à extração de dados do objeto retornado após a leitura do arquivo “.raw”. Dentre todos os dados fornecidos foi necessário retirar, especificamente, o “trace” referente a grandeza de interesse (no caso, tensão de saída) e organizar cada elemento do trace (isto é, passos de simulação dentro de cada simulação) em uma célula de um dataframe. Não foi necessário remover outliers ou normalizar dados, embora tenha sido aplicado o PAA (Piecewise Aggragate Aproximation) para reduzir o tempo de processamento através da redução da quantidade de informações suficientemente semelhantes.

O dataframe obtido após a aplicação do PAA possui o seguinte comportamento:



***(Figura: Valores de Vout de cada passo de simulação plotados individualmente)***

Onde a separação das simulações por grupos de falhas se torna bem evidente.

***Implementation***

**Utilities**

In utility.py, I have implemented utilities to handle common tasks.

**Delta** is an array of directions. Each item in Delta is a pair of (row direction, column direction). For example, [ -1, 0 ] means North direction.

Delta = [[-1, 0], # go north

[ 0, 1], # go east

[ 1, 0], # go south

[ 0, -1]] # go west

A change in direction can be expressed by an index move in Delta. For example, a right turn means adding 1 to the index. When the current direction is North (index=0), a right turn results in the direction change to East (index=1).

**Steering** is an Enum class for direction change. Rather than remembering what -1 means, I can simply use Steering.L to mean a left turn.

class Steering(Enum):

L, F, R = (-1,0,1) # Left, Forward, Right

def str (self):

return self.name

**Direction** is an Enum class for direction. The enum value of this class corresponds to the index values in Delta so that I do not need to remember the actual index value and use the Enum name instead. This class handles direction manipulation operations such as reversing direction or adjusting to change the direction by a Steering value.

class Direction(Enum):

N, E, S, W = range(4) # North, East, South, West

def reverse(self):

return Direction((self.value+2)%4)

def adjust(self, steering):

return Direction((self.value+steering.value)%4)

def delta(self):

return Delta[self.value]

def steer(self, direction):

diff = direction.value - self.value if diff ==3:

diff = -1 if diff ==-3:

diff = 1

return Steering(diff)

def str (self):

return self.name

The robot decides direction and moves its location. **Heading** is a class that encapsulates both direction and location. It is mutable and as such all methods will return a new Heading object.

class Heading(object):

def init (self, direction, location): self.direction = direction self.location = location

def str (self):

return '{} @ ({:>2d},{:>2d})'.format(

self.direction.name, self.location[0], self.location[1])

def adjust(self, steering, movement):

direction = self.direction.adjust(steering)

delta = direction.delta()

location = [ self.location[i]+delta[i]\*movement for i in range(2) ]

return Heading(direction, location)

# move forward

def forward(self, movement=1):

return self.adjust(Steering.F, movement)

# move to left

def left(self, movement=1):

return self.adjust(Steering.L, movement)

# move to right

def right(self, movement=1):

return self.adjust(Steering.R, movement)

# move backward with turning

def backward(self, movement=1):

return self.reverse().forward(movement)

# only reverse the direction def reverse(self):

return Heading(self.direction.reverse(), self.location)

The robot’s sensor values are given in a tuple format. Again, directly handling it can be error-prone. Making the code more human readable is a way to avoid such problems.

**Sensor** is a class that encapsulates sensor values. I can get a distance to a wall by specifying the steering value, and also find out if the robot is in a dead-end or not.

class Sensor:

def init (self, sensors):

self.sensors = sensors

def distance(self, steering):

steering\_sensor\_index\_map = { Steering.L : 0,

Steering.F : 1, Steering.R : 2

}

return self.sensors[steering\_sensor\_index\_map[steering]]

def isDeadEnd(self):

return max(self.sensors)==0

# both sides are walls def isOneWay(self):

return self.sensors[0]==0 and self.sensors[1]>0 and self.sensors[2]==0

def str (self):

return str(self.sensors)

**Goal** is a class that encapsulates the goal area in a maze so that I can check whether a location is in the goal area or not.

class Goal(object):

def init (self, rows, cols): self.goal\_row\_max = rows/2 self.goal\_row\_min = rows/2-1 self.goal\_col\_max = cols/2 self.goal\_col\_min = cols/2-1

def isGoal(self, location):

row, col = location

return self.goal\_row\_min <= row and row <= self.goal\_row\_max and \

self.goal\_col\_min <= col and col <= self.goal\_col\_max

**Grid** encapsulates two dimensional array so that I can associate maze locations to calculated values. I can get and set values using getValue and setValue methods, making the code readable that using the array index syntax.

class Grid(object):

def init (self, rows, cols ,init\_val):

self.rows = rows self.cols = cols

self.grid = [ [ copy.deepcopy(init\_val) for c in range(cols) ] for r in range(rows) ]

self.shape = (rows, cols)

def getitem (self, row):

return self.grid[row]

def getValue(self, location):

return self.grid[location[0]][location[1]]

def setValue(self, location, value):

self.grid[location[0]][location[1]] = value

def isValid(self, location):

row, col = location

return 0 <= row and row < self.rows and 0 <= col and col < self.cols

There are several subclass of Grid. Namely,

• **Mapper** for mapping the maze,

• **Counter** for counting the number of visits for each cell,

• **DeadEnd** for marking dead-end paths, and

• **Heuristic** to generate and holds the heuristic values

**A\* search**

In planner.py, I’ve implemented A\* star search (findOptimalMoves) to calculates the optimal moves from the start location to the goal area. Having a standalone program makes it easy to test the

search algorithm directly with the test maze files.

The program can be run by the planner.sh script as follows:

./plan.sh <maze\_number>

To find the optimal path and moves for the test\_maze\_01.txt, use the following:

./plan.sh 01

Mapper class can read the test maze file format so that the search algorithm knows where it can move to.



Note: it reads the maze file only when testing the A\* search logic. It will not do so while running the tester program to test the actual robot controllers.

A\* star search then uses Heuristic values and g-values to calculate f-values. The optimal path will be printed into the console as shown below:

-- Path --

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| , | , | , | , | , | , | , | , | , | , | , |
| , | , | , | , | , | , | , | , | , | , | , |
| , | , | , | , | , | , | , | , | , | , | , |
| , | , | , | , | , | , | , | , | , | , | , |
| , | , | , | , | , | , | , | , | , | , | , |
| , | , | , | , | , | ,\*,W, | | | , | , | , |
| , | , | , | , | , | , | ,N,W, | | | , | , |
| , | , | , | , | , | , | , ,N, | | | , | , |

, , , , , , , ,N,W,W,W

E,S, , ,E,E,S, , , , ,N

N,S, , ,N, ,E,S, , , ,N N,E,E,E,N, , ,E,E,E,E,N Path Length: 30

The optimal moves are returned in a list of (steering, movement) pairs. The list of moves can be applied from the start location to reach the goal with the minimum steps.

A sample is shown below for the test maze 01. The optimal path length is 30 but the actual moves required is only 17 since the robot can take up to 3 steps in one direction.

-- Moves -- (F,2)

(R,1) (R,2) (L,3) (L,2) (R,2) (R,1) (L,1) (R,1) (L,3) (F,1) (L,3) (L,3) (R,2) (L,1) (R,1) (L,1)

# of Moves: 17

***Refinement***

**Robot Controllers**

In controller.py, I defined a Controller base class which declares methods that the robot class interact with. There are various sub-classes of this class for specific logic implementations.

The following is a list of controllers used for the first run to explore the maze:

• **Controller\_Exploration** a base class for first run controllers

• **Controller\_Random** extends Controller\_Exploration to implement the random move

• **Controller\_DeadEnd** extends Controller\_Random with dead-end path detection

• **Controller\_Counter** extends Controller\_DeadEnd with the location visit counter allowing it to move to less visited locations for better exploration/expansion and avoid loops

• **Controller\_Heuristic** extends Controller\_Counter using the heuristic to decide direction when two possible directions has same counter value to reach the goal faster

In the second run, the robot internally switches to the following controller to reach to the goal following optimal moves calculated with the mapped area of the maze.

• **Controller\_Exploitation** uses the findOptimalMoves to get a list of optimal moves to follow based on the available information on the maze structure from the first run

**Robot**

The tester program can be run as follows:

./run.sh <controller\_name> <maze\_number> (<tick\_interval\_in\_seconds>)

For example, to run the random controller with maze 02:

./run.sh random 02

For debugging purpose, you can specify a delay seconds between each time step. The following adds 1 second between each time step so that you can actually follows the log messages.

./run.sh random 02 1

The following is a list of controller names:

• random

• deadend

• counter

• heuristic

Results

***Model Evaluation and Validation***

**Optimal Moves**

The optimal moves are measured by using the A\* search.

|  |  |  |
| --- | --- | --- |
| **Test maze** | **Path Length** | **Required Moves** |
| 01 | 30 | 17 |
| 02 | 43 | 23 |
| 03 | 49 | 25 |

The above numbers can be achieved if the robot has 100% mapping coverage of the maze as all robots are using the same search implementation in the 2nd run.

Maze 01 Optimal Moves

-- Path --

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, , , , , ,\*,W, , , ,

, , , , , , ,N,W, , ,

, , , , , , , ,N, , ,

, , , , , , , ,N,W,W,W E,S, , ,E,E,S, , , , ,N N,S, , ,N, ,E,S, , , ,N N,E,E,E,N, , ,E,E,E,E,N

Path Length! 30

-- Moves -- (F,2)

(R,1)

(R,2) (L,3) (L,2) (R,2) (R,1) (L,1) (R,1) (L,3) (F,1) (L,3) (L,3) (R,2) (L,1) (R,1) (L,1)

# of Moves! 17

There are alternate paths that have the same length (=30). The above move is selected as the A\*

search gives preference to straight paths by adding extra move cost to left and right turns.

For example, the following path’s length is 30 but the number of moves is 20 which is worse than the optimal moves by 3 steps.

-- Path --

, , , , , , , , , , ,

, , , , , , , ,E,S, ,

, , , , ,E,E,E,N,S, ,

, , , ,E,N, , ,S,W, ,

, , , ,N, , ,S,W, , , E,E,S, ,N, ,\*,W, , , , N, ,E,S,N, , , , , , , N, , ,E,N, , , , , , , N, , , , , , , , , , , N, , , , , , , , , , , N, , , , , , , , , , , N, , , , , , , , , , ,

Path Length! 30

-- Moves -- (F,3)

(F,3)

(R,2) (R,1) (L,1) (R,1) (L,1) (L,3) (F,1) (R,1) (L,1) (R,3) (L,1) (R,1) (R,2) (R,1) (L,1) (R,1) (L,1) (R,1)

# of Moves! 20

Maze 02 Optimal Moves

-- Path --

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, , , , , , , , , , , , ,

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, , , , , , , ,S,W,W,W,W,W

, , , , , ,S,W,W, , , , ,N

E,E,E,S, , ,\*, , , , , , ,N N, , ,E,S, , , , , , , , ,N N, , , ,S, , , , , , , ,E,N N, , , ,E,S, , , , , , ,N, N, , , , ,E,E,E,S, , , ,N, N, , , , , , , ,S, ,E,E,N, N, , , , , , , ,E,E,N, , , N, , , , , , , , , , , , ,

Path Length! 43

-- Moves -- (F,3)

(F,3)

(F,1) (R,3) (R,1) (L,1) (R,2) (L,1) (R,1) (L,3) (R,2)

(L,2) (L,1) (R,2) (L,3) (R,1) (L,3) (F,1) (L,3) (F,2) (L,1) (R,2) (L,1)

# of Moves! 23

Maze 03 Optimal Moves

-- Path --

E,E,E,E,E,E,E,S, , , , , , , ,

N, , , , , , ,E,S, , , , , , , N, , , , , , , ,E,E,E,E,S, , , N, , , , , , , , , , , ,S, , , N, , , , , , , , , , , ,S, , , N, , , , , , , , , , , ,E,E,S, N, , , , , , , , , , ,S,W,W,W, N, , , , , , , , , , ,S, , , , N, , , , , , , ,\*, ,S,W, , , , N, , , , , , , ,N,W,W, , , , , N, , , , , , , , , , , , , , , N,W,W, , , , , , , , , , , , , E,E,N, , , , , , , , , , , , , N, , , , , , , , , , , , , , , N, , , , , , , , , , , , , , , N, , , , , , , , , , , , , , ,

Path Length! 49

-- Moves -- (F,3)

(R,2) (L,1) (L,2) (R,3) (F,3) (F,3) (F,2) (R,3) (F,3) (F,1) (R,1) (L,1) (R,1) (L,3) (F,1) (R,3) (L,2) (R,1) (R,3) (L,2) (R,1) (L,1) (R,2) (R,1)

# of Moves! 25

Again, there can be a different path with the same number of moves. For example, the following path length is 45 (shorter than above) and it takes 25 moves (the same). The reason this was not chosen is because the list of moves contains less number of forward moves. In other words, there are more left and right turns which costs more than forward moves (in the physical micro mouse

-- Path --

, , , , , , , , , , , , ,

, , , , , , , , , , , , ,

, , , , , , , , , , , , ,

, , , , , , , ,S,W,W, , ,

, , , , , , , ,S, ,N, , ,

, , , , , ,S,W,W, ,N, , ,

, , , , , ,\*, , , ,N,W, ,

, , , , , , , , , , ,N,W,W

, , , , , , , , , , , ,E,N

, , , , , , , , , , , ,N, E,E,S, , ,E,E,E,S, , , ,N, N, ,E,S, ,N, , ,S, ,E,E,N, N, ,S,W, ,N, , ,E,E,N, , , N, ,E,E,E,N, , , , , , , ,

Path Length! 45

-- Moves -- (F,3)

(R,2) (R,1) (L,1) (R,1) (R,1) (L,1) (L,3) (L,3) (R,3) (R,2) (L,2) (L,1) (R,2) (L,3) (R,1) (L,1) (L,2) (R,1) (L,1) (R,3) (L,2) (L,2) (R,2) (L,1)

# of Moves! 25

**Random and Dead-End controllers**

Both the random and the dead-end controllers use random moves chosen from the available directions. As such, they give different outcome for every run. Moreover, it may or may not reach to the goal. I took 10 trial results to evaluate the average numbers for them.

**Random Controller**

The random controller does reach to the goal but not always. As the maze size increases, the success rate goes down. The robot turns left or right randomly at the dead-ends but it does not recognize the one-way path to them. Hence, it may repeatedly visit the same dead-ends over and over. After examining the log details, it became evident that the random logic spent lots of time in the dead end paths. Note: the below average values exclude rows with Goal=No.

Test Maze 01 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 831 | 95.14% | Yes | 30 | 17 | 44.767 |
| **2** | Yes | 210 | 66.67% | Yes | 34 | 21 | 28.067 |
| **3** | Yes | 111 | 38.19% | Yes | 34 | 21 | 24.767 |
| **4** | Yes | 108 | 43.06% | Yes | 30 | 21 | 24.667 |
| **5** | Yes | 179 | 56.25% | Yes | 30 | 17 | 23.033 |
| **6** | Yes | 638 | 89.58% | Yes | 30 | 17 | 38.333 |
| **7** | Yes | 60 | 36.11% | Yes | 32 | 19 | 21.067 |
| **8** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **9** | Yes | 256 | 72.92%% | Yes | 36 | 22 | 30.600 |
| **10** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **Average** | 80.00% | 299.125 | 60.71% | 80.00% | 32 | 19.375 | 29.413 |

Test Maze 02 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path**  **Length** | **Moves** |
| **1** | Yes | 399 | 86.22% | Yes | 43 | 26 | 39.367 |
| **2** | Yes | 172 | 52.55% | Yes | 49 | 31 | 36.800 |
| **3** | Yes | 258 | 55.61% | Yes | 47 | 31 | 39.667 |
| **4** | Yes | 251 | 50.51% | Yes | 47 | 30 | 38.433 |
| **5** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **6** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **7** | Yes | 737 | 72.45% | Yes | 43 | 25 | 49.633 |
| **8** | Yes | 805 | 89.29% | Yes | 43 | 23 | 49.900 |
| **9** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **10** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **Average** | 60.00% | 437 | 67.77% | 60.00% | 45.33 | 27.67 | 42.300 |

Test Maze 03 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **2** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **3** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **4** | Yes | 618 | 84.38% | Yes | 51 | 26 | 46.667 |
| **5** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **6** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **7** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **8** | Yes | 226 | 53.12% | Yes | 63 | 36 | 43.600 |
| **9** | Yes | 361 | 66.41% | Yes | 49 | 26 | 38.100 |
| **10** | Yes | 519 | 75.78%% | Yes | 51 | 31 | 48.367 |
| **Average** | 40.00% | 431 | 67.97% | 40.00% | 53.5 | 29.75 | 44.184 |

**Dead-End Controller**

The dead-end controller avoids dead-end paths by keep track of dead-end paths. As a result, the success rate is higher than the random controller. Having said that, it can still fail to reach the goal from time to time due to the random move choice. The mapping coverage is slightly higher than

the random controller, too. However, higher coverage does not always translates to better scoring in the 2nd run, indicating the robot needs better logic than just randomly wandering about.

It was observed that the dead-end controller spent lots of time in loops. We need a controller that avoid going through the same path again and again.

Test Maze 01 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 62 | 38.89% | Yes | 50 | 32 | 34.133 |
| **2** | Yes | 282 | 81.25% | Yes | 36 | 23 | 32.467 |
| **3** | Yes | 426 | 81.94% | Yes | 30 | 17 | 31.267 |
| **4** | Yes | 227 | 81.25% | Yes | 36 | 23 | 30.633 |
| **5** | Yes | 545 | 92.36% | Yes | 30 | 17 | 35.233 |
| **6** | Yes | 267 | 66.67% | Yes | 30 | 17 | 25.967 |
| **7** | Yes | 147 | 56.25% | Yes | 38 | 22 | 26.967 |
| **8** | Yes | 137 | 60.42% | Yes | 38 | 25 | 29.633 |
| **9** | Yes | 972 | 97.92% | Yes | 30 | 17 | 49.467 |
| **10** | Yes | 258 | 76.39% | Yes | 32 | 21 | 29.667 |
| **Average** | 100.00% | 332.300 | 73.33% | 100.00% | 35.00 | 21.400 | 32.543 |

Test Maze 02 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 440 | 67.86% | Yes | 45 | 25 | 39.733 |
| **2** | Yes | 180 | 50.51% | Yes | 49 | 31 | 37.067 |
| **3** | Yes | 533 | 79.59% | Yes | 43 | 25 | 42.833 |
| **4** | Yes | 827 | 91.33% | Yes | 47 | 28 | 55.633 |
| **5** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **6** | Yes | 97 | 41.33% | Yes | 61 | 36 | 39.300 |
| **7** | Yes | 517 | 82.14% | Yes | 43 | 27 | 44.300 |
| **8** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **9** | Yes | 490 | 59.18% | Yes | 43 | 28 | 44.400 |
| **10** | No | n/a | n/a | n/a | n/a | n/a | n/a |
| **Average** | 70.00% | 440.571 | 67.42% | 70.00% | 47.29 | 28.571 | 43.324 |

Test Maze 03 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 348 | 69.53% | Yes | 59 | 31 | 42.667 |
| **2** | Yes | 178 | 48.83% | Yes | 57 | 33 | 39.000 |
| **3** | Yes | 188 | 39.45% | Yes | 49 | 28 | 34.333 |
| **4** | Yes | 913 | 85.55% | Yes | 51 | 25 | 55.500 |
| **5** | Yes | 333 | 59.77% | Yes | 53 | 29 | 40.167 |
| **6** | Yes | 584 | 85.16% | Yes | 51 | 28 | 47.533 |
| **7** | Yes | 703 | 85.55% | Yes | 51 | 26 | 49.500 |
| **8** | Yes | 473 | 76.56% | Yes | 51 | 29 | 44.833 |
| **9** | Yes | 305 | 58.59% | Yes | 59 | 31 | 41.233 |
| **10** | Yes | 676 | 87.89% | Yes | 53 | 29 | 51.600 |
| **Average** | 100.00% | 470.100 | 69.69% | 100.00% | 53.40 | 28.900 | 44.637 |

**Dead-End Controller Part 2**

I’ve experimented with the dead-end controller by making it back off from the dead-ends with negative movement value. The idea is using one back off move rather than turn left or right twice to move away from the dead-ends. This proves to be a bad idea after observing the log. When the robot backs off and moves out of a dead-end, it can only move either left or right as the forward move will bring it back into the dead-end path, limiting the move options to maximum 2. It is

actually better to turn left or right at dead-ends just like the original controller does. Then, when the robot is moving out of the dead-end path, it has maximum 3 directional options making the exploration more effective.

**Counter and Heuristic controllers**

The counter controller and the heuristic controller have no randomness. They give the same results every time. Therefore, I measured their performances by one trial for each controller.

**Counter Controller**

The counter controller keeps track of how often each location has been visited and explores less visited locations. The coverage rate is high with less moves than previous controllers in the maze

01 and the maze 02. The controller is avoiding loops very well.

However, it does a bad job in the test maze 03 because it is not aware of where the goal is and earnestly exploring the maze away from the goal.

Test Maze 01 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 170 | 86.11% | Yes | 32 | 17 | 22.733 |

Test Maze 02 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 378 | 91.84% | Yes | 45 | 27 | 39.667 |

Test Maze 03 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 806 | 98.83% | Yes | 51 | 25 | 51.933 |

**Heuristic Controller**

The heuristic controller uses the heuristic values to guide the robot to move towards the goal. When there are two directions where both has the same counter value, it will choose the one with a smaller heuristic value.

The result is much better than any other controllers in all mazes. Test Maze 01 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 103 | 54.17% | Yes | 34 | 18 | 21.500 |

Test Maze 02 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 183 | 68.37% | Yes | 47 | 29 | 35.167 |

Test Maze 03 Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 109 | 35.55% | Yes | 59 | 33 | 36.700 |

***Justification***

The best performing controller is the heuristic controller in terms of the score value. The below table compares the result with the best path length and optimal moves for each test maze.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Test maze** | **Best Path**  **Length** | **Best Path**  **Optimal Moves** | **Heuristic**  **Controller**  **Path Length** | **Heuristic**  **Controller**  **Moves** |
| 01 | 30 | 17 | 34 | 18 |
| 02 | 43 | 23 | 47 | 29 |
| 03 | 49 | 25 | 59 | 33 |

The heuristic controller uses much less moves in the first run than any other controllers and yet it can achieve good moves to take the robot to the goal in the second run.

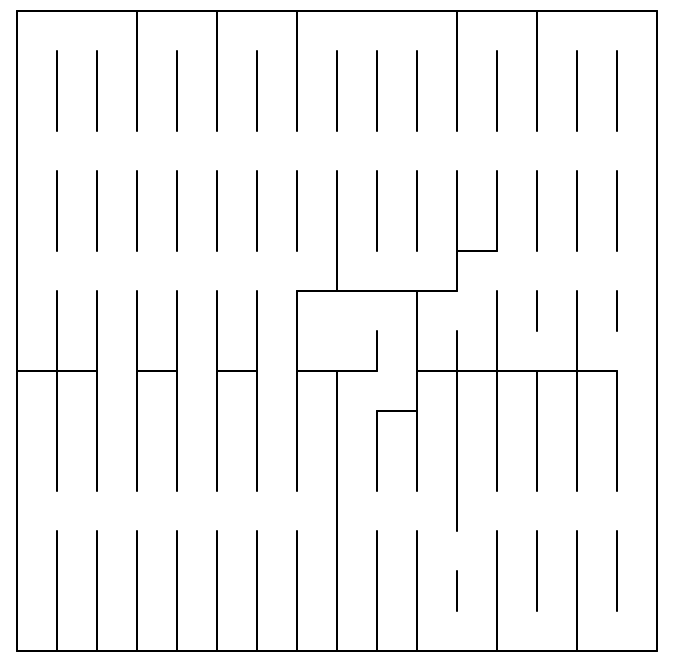
Conclusion

***Free-Form Visualization***

It is easily possible to make a maze more difficult for particular expansion/goal-seeking logic. I

came up with a new maze (Maze 04) to prove that point as shown below.

**Maze 04 (16x16)**



This maze has many dead-ends and loops. The random controller performs very badly in this maze with low success rate. The dead-end controller performs much better but not as good as the counter controller since there are many loops in this maze. The heuristic controller performs much better than the random controller and the dead-end controller.

Test Maze 04 Results for Heuristic Controller

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 370 | 76.17% | Yes | 52 | 25 | 37.400 |

Unlike with the test maze 03 (109 moves in the first run), the heuristic controller spent 370 moves in the first run, indicating the heuristic controller was not very fast to find the goal in this maze.

This result is expected as I actually made the maze really hard for the heuristic controller. The below diagram of the optimal moves for the test maze 04 shows the reason why.

-- Path --

, , , , , , , , , , , , , , ,

, , , , , , , , , , , , , , ,

, , , , , , , , , , , , , , ,

, , , , , ,E,E,E,E,E,E,E,E,E,S

, , , , , ,N, , , , , , , , ,S

, , , , , ,N, , , , , , , , ,S

, , , , , ,N, , , , , , , , ,S

, , , , , ,N, ,\*,W, , , , , ,S

, , , , , ,N, , ,N, , , , , ,S

, , , , , ,N, ,E,N, , , , , ,S

, , , , , ,N, ,N, , , , , , ,S

, , , , , ,N, ,N, , , , , , ,S

E,E,E,E,E,E,N, ,N,W,W,S,W,W,W,W N, , , , , , , , , ,N,W, , , , N, , , , , , , , , , , , , , , N, , , , , , , , , , , , , , ,

Path Length! 52

-- Moves -- (F,3)

(R,3)

(F,3) (L,3) (F,3) (F,3) (R,3) (F,3) (F,3) (R,3) (F,3) (F,3) (R,3) (F,1) (L,1) (R,1) (R,1) (L,2) (R,3) (R,1) (L,2) (L,1)

# of Moves! 22

The optimal path to the goal requires the robot to go almost full circle around the goal area, making the heuristic values less useful.

The counter controller, however, performs better than the heuristic controller in this maze: Test Maze 04 Results for Counter Controller

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Trial** | **1st Run** | | | **2nd Run** | | | **Score** |
| **Goal?** | **Moves** | **Coverage** | **Goal?** | **Path Length** | **Moves** |
| **1** | Yes | 145 | 48.83% | Yes | 74 | 31 | 35.900 |

The counter controller spent only 145 moves in the first run. The second run of the counter controller is much worse than that of the heuristic controller. But the counter controller outperforms the heuristic controller in the first run by large.

The reason for the counter controller to performs better than the heuristic controller in this maze was because it has no bias for the goal location which is advantage of the heuristic controller in other mazes.

***Reflection***

The initial challenge for me was to divide the project into smaller problems to tackle with. I’ve decided to have separate test program for the A\* search program as I realized it does not require a running robot to test the search algorithm. Then, I’ve divided each enhancements to the robot controller into different python classes making it easier to add improvements in terms of coding and also the actual test scores. Throughout the project, I was making common tasks into utility classes so that I do not need to write similar logic or handling in different places (i.e. Direction, Steering, Sensor, Grid).

The next challenge for me was to find problems in expanding the maze mapping area. I had issues like dead-ends and looping. Over the time, I’ve added effective logging to analyse the robot behaviour and look for potential issues. This was largely a trial-and-error process for me since I did not have much experience in the maze solving problem before. It was a great learning process for me.

Finally, the most difficult and interesting part was how to expand the mapping area of the maze while reaching to the goal at minimum time required in the first run. Unlike in the second run, where the robot simply uses A\* search to find the optimal path and travel to the goal accordingly, the first run was full of challenges due to the unknown area to be explored. Overall, I built a series

of controllers to add improvement bit by bit making the process simpler than without such structural

approach to solve the main problem. I believe the final controller gives fine performance in the real micro mouse scenario with some improvement for continuous domain support.

***Improvement***

In this project, everything (time, location, move and turn) is in a discrete domain. In the real micro mouse competition, everything is in a continuous domain.

For example, the distance from the robot to the wall is measured in continuous value with some sensor errors. The robot movement itself would have some randomness. Therefore, the robot would need to perform SLAM (simultaneous localization and mapping) to explore the maze.

Moreover, the robot needs to use PID control to continuously adjust the direction and turns so that it

can wander around in the maze without colliding with the walls. The speed needs to be controlled rather than just number of steps. Turns will be continuous rotations. Moreover, the robot may be able to move diagonally rather than zigzag which is not allowed in the discrete domain.

Talking about the real micro mouse competition, the fact that the robots are physical adds many more complexity. The path finding logic is probably one of the easiest part of the whole robot construction. There are many aspects to take care in physical robots: what sensors to use, what kind of motors and how heavy it can be, how much memory size available to use, etc. Maybe I could have a sensor rotating on top of the robot mapping neighboring areas simultaneously just like a google car. The possibilities are endless.