# Capstone Project of Machine Learning Engineer Nanodegree: Plot and Navigate a Virtual Maze

Yi-Yuan Liang

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## 1 Definition

There are three subsections in this section. They are: *Project Overview*, *Problem Statement*, and *Metrics*.

### 1.1 Project Overview

The purpose of this project is to design a virtual robot to navigate a given maze. The task of the robot is to plot a path from a corner of the maze to the center. Two runs are allowed. In the first run, the robot has to find the goal and the best path from corner to center. In the second run, the robot attempts to reach the center in the fastest time possible, using what it has learned in the first run. This rule is inspired from the APEC Micromouse Contest [1].

### 1.2 Problem Statement

As mentioned in the previous section, two runs are allowed for the robot. In the first run, the robot is allowed to freely roam the maze to build a map of the maze. It must enter the goal room at some point during its exploration, but is free to continue exploring the maze after finding the goal. After entering the goal room, the robot may choose to end its exploration at any time. The robot is then moved back to the starting position and

orientation for its second run. Its objective now is to go from the start position to the goal room in the fastest time possible.

Since a robot finding a path from start to goal could be viewed as a search problem [4], two kinds of search algorithms were implemented for this project. One is *depth-first search* (DFS) [7], the other is *A-star search algorithm* [2]. Using DFS, the robot can always find the goal, however, the time performance is not particular well. On the other hand, using A-star search, the robot makes an obvious improvement than using DFS. The details of these algorithms and the simulation results will be demonstrated in the following sections.

### 1.3 Metrics

The robot's score for the maze is equal to the *number of time steps required to execute the second run* ($t_2$), plus one thirtieth the *number of time steps required to execute the first run* ($t_1$). A maximum of one thousand time steps is allotted to complete both runs for a single maze.

The score can be formulated as:

$$\text{score} = \frac{1}{30}t_1 + t2.$$

That means the score is a weighted sum of $t_1$ and $t_2$. Besides, $t_2$ dominates the final score. I recognize $t_1$ as an investment. That is, it is worth for a robot to invest time in first run in order to save time in second run. Specifically, if a robot spends 30 more steps in first run, but it can save more than one time step in second run, the investment is worth.

The scoring method is adequate for this project or the contest [1]. Because the robot does not aware of the maze previously, the purpose of first run is to test the robot whether it can find a path from start to goal. More importantly, to test the robot whether it can find a shortest path for its second run. It is hard to find the real shortest path for the robot, if it does not navigate the most regions of the maze in the first run. Therefore, we should not punish the robot for its investment in first run. This is why the scoring formula is designed as a weighted sum of $t_1$ and $t_2$.

## 2 Analysis

There are three subsections in this section. They are: *Data Exploration and Visualization*, *Algorithms and Techniques*, and *Benchmark*.

### 2.1 Data Exploration and Visualization

The given mazes are specified and coded in the files with text format. On the first line of the text file is a number, $n$, describing the number of squares on each dimension of the maze.

On the following $n$ lines are $n$ comma-delimited four-bit coding numbers describing which edges of the square are open to movement. The coding method is described as below. Each number represents a four-bit number that has a bit value of 0 if an edge is closed (walled) and 1 if an edge is open (no wall); the 1s register corresponds with the upwards-facing side, the 2s register the right side, the 4s register the bottom side, and the 8s register the left side.

Figure 1 is a portion of an example of four-bit coding maze, in the bottom left corner, the number 1 means the upper edge of this square is open, 6 means both the right edge and the bottom edge are open.

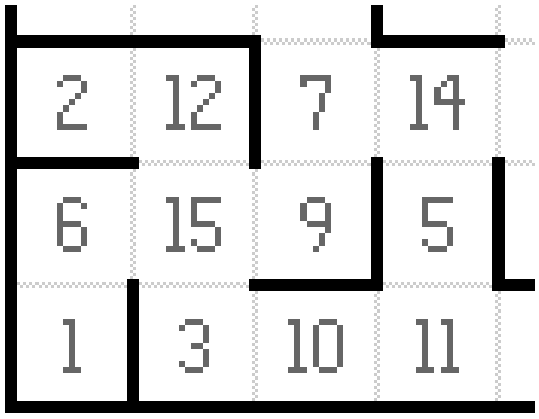
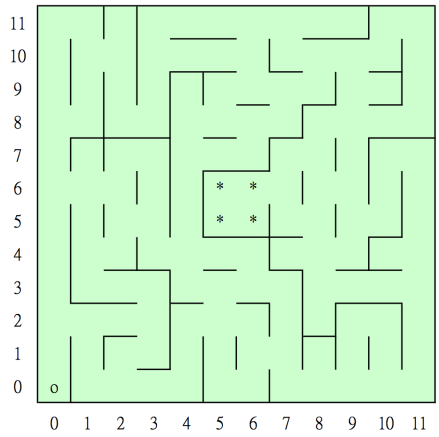



Figure 1: A portion of an example of four-bit coding maze.

From this coding method, we are easily to translate the given four-bit coding maze into

```
12
1,5,7,5,5,5,7,5,7,5,5,6
3,5,14,3,7,5,15,4,9,5,7,12
11,6,10,10,9,7,13,6,3,5,13,4
10,9,13,12,3,13,5,12,9,5,7,6
9,5,6,3,15,5,5,7,7,4,10,10
3,5,15,14,10,3,6,10,11,6,10,10
9,7,12,11,12,9,14,9,14,11,13,14
3,13,5,12,2,3,13,6,9,14,3,14
11,4,1,7,15,13,7,13,6,9,14,10
11,5,6,10,9,7,13,5,15,7,14,8
11,5,12,10,2,9,5,6,10,8,9,6
9,5,5,13,13,5,5,12,9,5,5,12
```

(a) Four-bit coding edition of Maze01. (The given format)




(b) Normal edition of Maze01. The start is labeled as 'o' and the goal is labels as '*'.

Figure 2: The four-bit coding representation and the normal wall representation of Maze01.

human understandable mazes specified by walls. Figure 2a is the four-bit coding edition of Maze01; and Figure 2b is the normal one.

As for robot, it has three obstacle sensors, mounted on the front of the robot, its right side, and its left side. Obstacle sensors detect the number of open squares in the direction of the sensor; for example, in its starting position, the robot's left and right sensors will state that there are no open squares in those directions and at least one square towards its front. On each time step of the simulation, the robot may choose to rotate clockwise or counterclockwise ninety degrees, then move forwards or backwards a distance of up to three units. It is assumed that the robot's turning and movement is perfect. If the robot tries to move into a wall, the robot stays where it is. After movement, one time step has passed, and the sensors return readings for the open squares in the robot's new location and/or orientation to start the next time unit.

After understand the sensing method of robot, let's take a look at maze01 more detail. The start location is $(0, 0)$, and the goal is a square with four positions, they are $(5, 5)$, $(5, 6)$, $(6, 5)$, $(6, 6)$. When navigating such a maze, a robot may encounters at least two kinds of hazards. I named them as: *dead-end hazard* and *loop hazard*. When a robot encounters a

dead-end hazard, it has no way for any direction except moves backwards. For example, when the robot get into the position $(1, 7)$, $(4, 9)$, $(8, 1)$, or $(10, 9)$, it encounters a dead-end hazard. The other hazard is loop hazard, which is caused by isolated walls. For example, the right-hand-side wall of position $(0, 9)$ and $(0, 10)$ may causes loop hazard. Our robots should avoid these hazards in the second run.

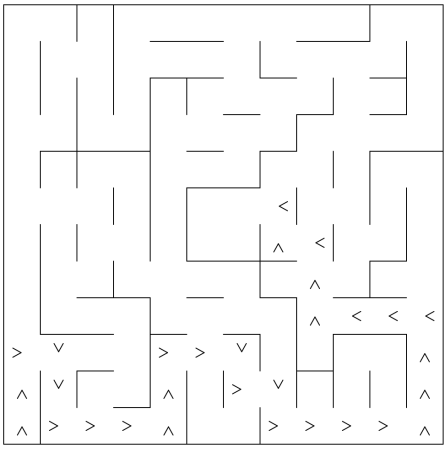
There are many paths for a robot to reach the goal. I just list three of them as shown in Figure 3a, 3c, 3e. Because the robot can move up to three units, the moving steps can be reduced. When the steps of a path are reduced, I call this path as an optimized path (Figure 3b, 3d, 3f).

The shortest path of maze01 is path-1 (Figure 3a); it takes 30 steps. After optimization, only 17 steps are required (Figure 3b).

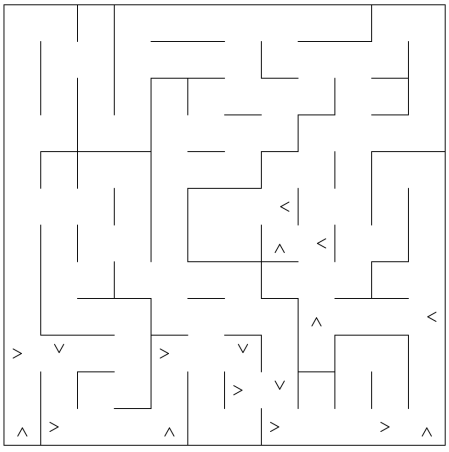
### 2.2 Algorithms and Techniques

A robot finding a path from start to goal could be viewed as a search problem [5]. There are many search algorithms could be used to solve a robot path-planning problem, including *best-first search* (BFS), *uniform cost search* (UCS), *depth-first search* (DFS), and *depth-limited search* (DLS), etc [3]. These algorithms belong to *blind searches*, because during the search procedure, there is no additional information obtained. On the other hand, some kind of search algorithms called *heuristic searches*, because during the search procedure, there are additional information could be obtained. A well-known heuristic search algorithm is the A-star search [4], which will be used in this project. Except A-star search algorithm, DFS will also be implemented for the purpose of benchmarking.

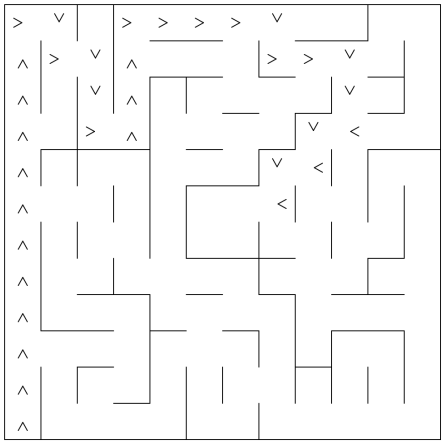
A DFS could be implemented as a recursive or a non-recursive procedure. I used the non-recursive one. Notably, a maze could be viewed as a graph; all positions within the maze are interpreted as vertices or nodes of the graph. Besides, for any position, its *adjacent vertices* are the positions that can be arrived for a robot within one step. *Adjacent edges* of a node link the node and its adjacent vertices. The following is the pseudo code of DFS [7].



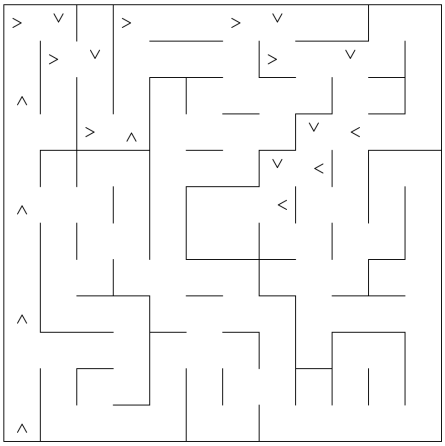
(a) Maze01: path-1 (30 steps)



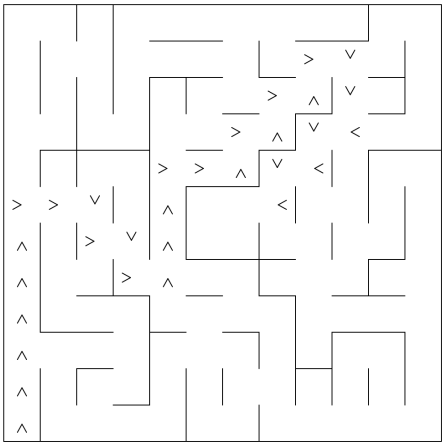
(b) Maze01: path-1 optimized (17 steps)



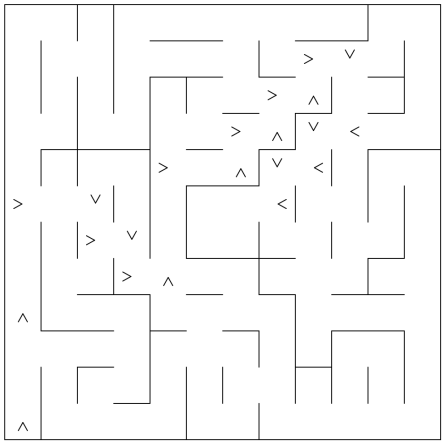
(c) Maze01: path-2 (34 steps)



(d) Maze01: path-2 optimized (20 steps)



(e) Maze01: path-3 (30 steps)



(f) Maze01: path-3 optimized (21 steps)

Figure 3: Example Paths of Maze01

```
1  procedure DFS-iterative(G,v):
2      let S be a stack
3      S.push(v)
4      while S is not empty
5          v = S.pop()
6          if v is not labeled as discovered:
7              label v as discovered
8              for all edges from v to w in G.adjacentEdges(v) do
9                  S.push(w)
```

The inputs of the above algorithm are $G$ and $v$, where $G$ is a graph, $v$ is a vertex of the graph. In our case, $G$ is the maze that can be represented as a graph, $v$ is the starting position. From the start, DFS begins to traverse the maze in a uniform turning order, e.g., `up`, `right`, `down`, and `left`. Besides, it explores as far as possible along each branch of turning before backtracking. Using DFS, the robot can always find the goal.

As for A-star search, the following is the pseudo code [2].

```
1   initialize the open list
2   initialize the closed list
3   put the starting node on the open list (you can leave its f at zero)

4   while the open list is not empty
5       find the node with the least f on the open list, call it "q"
6       pop q off the open list
7       generate q's successors and set their parents to q
8       for each successor
9         if successor is the goal, stop the search
10          successor.g = q.g + distance between successor and q
11          successor.h = distance from goal to successor
```

```
12          successor.f = successor.g + successor.h

13          if a node with the same position as successor is in the OPEN list \
14              which has a lower f than successor, skip this successor
15          if a node with the same position as successor is in the CLOSED list \
16              which has a lower f than successor, skip this successor
17          otherwise, add the node to the open list
18      end
19      push q on the closed list
20  end
```

The above algorithm is called a heuristic algorithm because during the search, additional heuristic information about the search problem (e.g., the structure of the maze) is introduced. Line 11 records heuristic value `successor.h` as the distance from goal to successor. The distance cannot be obtained if we do not know the structure of the maze. Therefore, adopting additional heuristic information, the robot can proceed preferentially through nodes of the maze graph that problem-specific information indicates might be on the best path to the goal.

## 2.3 Benchmark

In this subsection, I will discuss what is a reasonable benchmark score I feel. I will use the three examples stated in Section 2.1 to demonstrate what the optimal scores they could be along with the reasonable score range they perhaps will be.

As mentioned in Section 1.3, the robot's score for the maze is equal to the number of time steps required to execute the second run, plus one thirtieth the number of time steps required to execute the first run. Therefore, the scores for the paths stated in Section 2.1 should be as shown in the Table 1.

Table 1: The scores of path-1, path-2, and path-3.

| | Best scores | Reasonable scores |
|---|---|---|
| path-1 | 18 | $22 \sim 27$ |
| path-2 | 21.13 | $25.67 \sim 31.33$ |
| path-3 | 22 | $26 \sim 31$ |

# 3 Methodology

In this section, there are three subsections; they are: *Data Preprocessing*, *Implementation*, and *Refinement*.

## 3.1 Data Preprocessing

Because the sensor specification and environment designs are provided, there is no data preprocessing needed in this project.

## 3.2 Implementation

The python scripts along with test mazes for this project includes the following files:

- robot.py: This script establishes the robot class. This is the only script I have modified.
- maze.py: The provided script contains functions for constructing the maze and for checking for walls upon robot movement or sensing.
- tester.py: The provided script runs to test the robot's ability to navigate mazes.
- showmaze.py: The provided script is used to create a visual demonstration of what a maze looks like.
- test_maze_01.txt $\sim$ test_maze_03.txt: The three provided sample files specify mazes upon which to test my robot.

- test_maze_04.txt: The 12x12 maze which is designed by myself for testing the robustness of my robot.

In order to understand the architecture of the robot environments, I plot a diagram as shown in Figure 4. The file `tester.py` is the tester of the whole environment. Tester can call the `Maze` class (`maze.py`) to obtain the given maze. Then, the tester can initialize a robot (`robot.py`), and send the only parameter, the dimension of the maze, to the robot. While a robot has been initialized, its location and heading is always $(0, 0)$ and 'up', respectively.

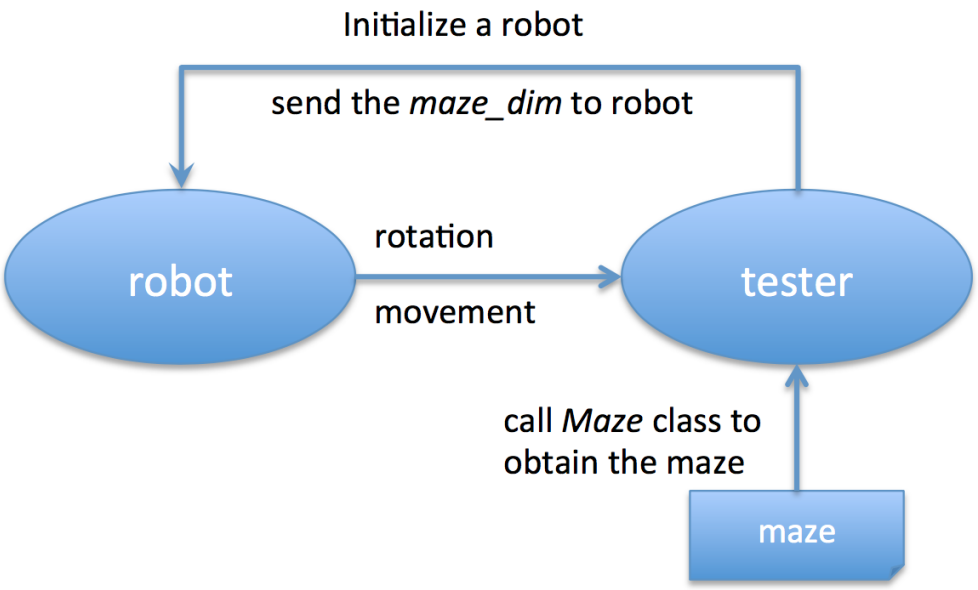



Figure 4: The architecture of the robot and the test environment.

For the purpose of clarity, I summarize some of the characteristics of the robot as below.

- The robot is always initialized by the tester. While the robot is initialized, its location is $(0, 0)$ and heading is 'up'.
- The robot does not know any information about the given maze except the dimension. Of course, the maze is always a square.

- The robot has to maintain the map of the maze when it visiting the maze.
- The robot has three sensors mounted on the front of the robot, its right side, and its left side. These sensors can detect the distances from the robot to walls.
- I implemented only one method (function), `next_move`, for the `Robot` class. (Except the constructor, of course.)
- The `next_move` function must then return two values indicating the robot's rotation and movement on that time-step. Rotation is expected to be an integer taking one of three values: $-90$, 90, or 0, indicating a counterclockwise, clockwise, or no rotation, respectively. Movement follows rotation, and is expected to be an integer in the range $[-3, 3]$ inclusive.
- The robot will attempt to move that many squares forward (positive) or backwards (negative), stopping movement if it encounters a wall.

The search algorithms implemented for the robot are DFS and A-star. In some sense, my DFS could be viewed as an A-star using heuristic matrix with 0 in each entry. For an A-star search, the heuristic matrix plays a very important role in getting a good performance. I particularly mention my design of the heuristic matrix here.

For a $n \times n$ maze, my heuristic matrix, $H(i, j)$, is defined as below:

$$\begin{aligned} H(i,j) = \min(&\|(i,j) - (\frac{n}{2} - 1, \frac{n}{2} - 1)\|, \\ &\|(i,j) - (\frac{n}{2} - 1, \frac{n}{2})\|, \\ &\|(i,j) - (\frac{n}{2}, \frac{n}{2} - 1)\|, \\ &\|(i,j) - (\frac{n}{2}, \frac{n}{2})\|), \end{aligned}$$

where $\|\cdot\|$ is 1-norm, which is defined as:

$$\|\mathbf{v}\| = \sum_{i=0}^{k} |v_i| \,,$$

where $\mathbf{v} = (v_0, v_1, v_2, \ldots, v_k)$.

In particular, the heuristic matrix for $12 \times 12$ maze is defined as:

$$\begin{bmatrix} 10 & 9 & 8 & 7 & 6 & 5 & 5 & 6 & 7 & 8 & 9 & 10 \\ 9 & 8 & 7 & 6 & 5 & 4 & 4 & 5 & 6 & 7 & 8 & 9 \\ 8 & 7 & 6 & 5 & 4 & 3 & 3 & 4 & 5 & 6 & 7 & 8 \\ 7 & 6 & 5 & 4 & 3 & 2 & 2 & 3 & 4 & 5 & 6 & 7 \\ 6 & 5 & 4 & 3 & 2 & 1 & 1 & 2 & 3 & 4 & 5 & 6 \\ 5 & 4 & 3 & 2 & 1 & 0 & 0 & 1 & 2 & 3 & 4 & 5 \\ 5 & 4 & 3 & 2 & 1 & 0 & 0 & 1 & 2 & 3 & 4 & 5 \\ 6 & 5 & 4 & 3 & 2 & 1 & 1 & 2 & 3 & 4 & 5 & 6 \\ 7 & 6 & 5 & 4 & 3 & 2 & 2 & 3 & 4 & 5 & 6 & 7 \\ 8 & 7 & 6 & 5 & 4 & 3 & 3 & 4 & 5 & 6 & 7 & 8 \\ 9 & 8 & 7 & 6 & 5 & 4 & 4 & 5 & 6 & 7 & 8 & 9 \\ 10 & 9 & 8 & 7 & 6 & 5 & 5 & 6 & 7 & 8 & 9 & 10 \end{bmatrix}$$

Now, we apply the heuristic matrix to the three given mazes, a preliminary result could be obtained. The following is the result while Maze01 is tested.

```
********************************************************************************
Starting run 0.
[(0, 0), 'up'],
[(0, 1), 'up'],
[(0, 2), 'up'],
[(0, 3), 'up'],
[(0, 4), 'up'],
[(0, 5), 'up'],
[(0, 6), 'right'],
[(1, 6), 'right'],
[(2, 6), 'down'],
[(2, 5), 'right'],
[(3, 5), 'up'],
[(3, 6), 'up'],
[(3, 7), 'left'],
```

```
[(2, 7), 'left'],
[(3, 7), 'up'],
[(3, 7), 'up'],
[(3, 6), 'up'],
[(3, 6), 'up'],
[(3, 5), 'right'],
[(3, 5), 'down'],
[(3, 4), 'right'],
[(4, 4), 'up'],
[(4, 5), 'up'],
[(4, 6), 'up'],
[(4, 7), 'right'],
[(5, 7), 'right'],
[(6, 7), 'up'],
[(6, 8), 'left'],
[(5, 8), 'left'],
[(4, 8), 'up'],
[(4, 9), 'up'],
[(4, 8), 'left'],
[(4, 8), 'left'],
[(5, 8), 'left'],
[(5, 8), 'up'],
[(5, 9), 'right'],
[(6, 9), 'up'],
[(6, 10), 'left'],
[(5, 10), 'left'],
[(4, 10), 'left'],
[(3, 10), 'down'],
```

```
[(3, 9), 'down'],
[(3, 8), 'left'],
[(2, 8), 'up'],
[(2, 9), 'up'],
[(2, 10), 'left'],
[(1, 10), 'down'],
[(1, 9), 'down'],
[(1, 8), 'left'],
[(0, 8), 'down'],
[(0, 7), 'down'],
[(0, 8), 'left'],
[(0, 8), 'up'],
[(0, 9), 'up'],
[(0, 10), 'up'],
[(0, 11), 'right'],
[(1, 11), 'right'],
[(0, 11), 'up'],
[(0, 11), 'up'],
[(0, 10), 'up'],
[(0, 10), 'up'],
[(0, 9), 'up'],
[(0, 9), 'up'],
[(0, 8), 'left'],
[(0, 8), 'left'],
[(1, 8), 'down'],
[(1, 8), 'down'],
[(1, 9), 'down'],
[(1, 9), 'down'],
```

```
[(1, 10), 'left'],
[(1, 10), 'left'],
[(2, 10), 'up'],
[(2, 10), 'up'],
[(2, 11), 'up'],
[(2, 10), 'up'],
[(2, 10), 'up'],
[(2, 9), 'up'],
[(2, 9), 'up'],
[(2, 8), 'left'],
[(2, 8), 'left'],
[(3, 8), 'down'],
[(3, 8), 'down'],
[(3, 9), 'down'],
[(3, 9), 'down'],
[(3, 10), 'left'],
[(3, 10), 'up'],
[(3, 11), 'right'],
[(4, 11), 'right'],
[(5, 11), 'right'],
[(6, 11), 'right'],
[(7, 11), 'down'],
[(7, 10), 'right'],
[(8, 10), 'down'],
[(8, 9), 'left'],
[(7, 9), 'down'],
[(7, 8), 'down'],
[(7, 9), 'left'],
```

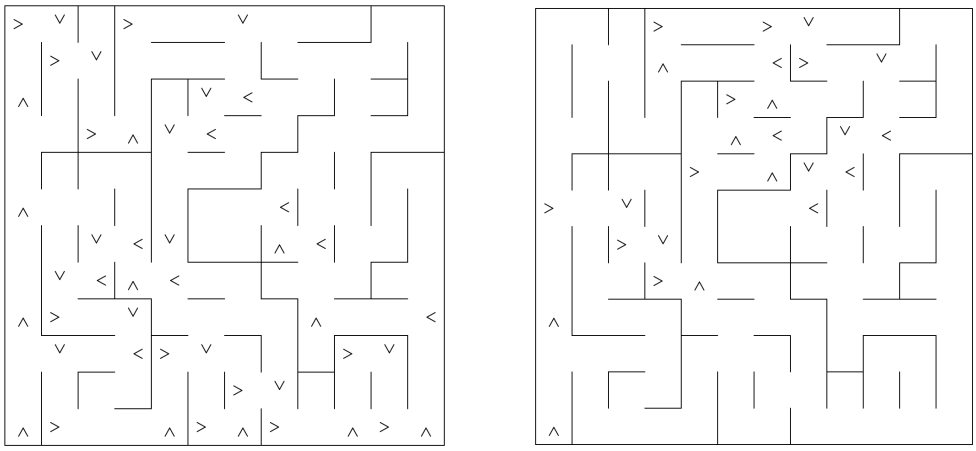
```
[(7, 9), 'left'],
[(8, 9), 'down'],
[(8, 9), 'down'],
[(8, 10), 'right'],
[(8, 10), 'right'],
[(9, 10), 'down'],
[(9, 9), 'down'],
[(9, 8), 'left'],
[(8, 8), 'down'],
[(8, 7), 'left'],
[(7, 7), 'down'],
[(7, 6), 'left'],
[(6, 6), 'up'],
Ending first run. Starting next run.
Starting run 1.
[(0, 0), 'up'],
[(0, 3), 'up'],
[(0, 6), 'right'],
[(2, 6), 'down'],
[(2, 5), 'right'],
[(3, 5), 'down'],
[(3, 4), 'right'],
[(4, 4), 'up'],
[(4, 7), 'right'],
[(6, 7), 'up'],
[(6, 8), 'left'],
[(5, 8), 'up'],
[(5, 9), 'right'],
```

Table 2: The simulation results on the three given mazes.

| | | Maze-01 | Maze-02 | Maze-03 |
|---|---|---|---|---|
| DFS | score | 49.576 | 71.233 | 73.667 |
| | run-2 steps | 46 | 65 | 59 |
| A-star | score | 29.667 | 44.267 | 43.100 |
| | run-2 steps | 26 | 41 | 39 |

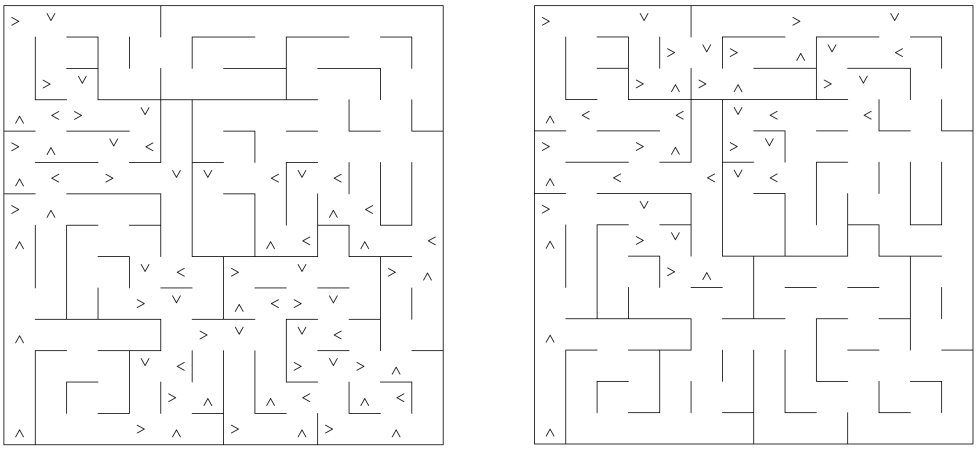
```
[(6, 9), 'up'],
[(6, 10), 'left'],
[(3, 10), 'up'],
[(3, 11), 'right'],
[(6, 11), 'right'],
[(7, 11), 'down'],
[(7, 10), 'right'],
[(9, 10), 'down'],
[(9, 8), 'left'],
[(8, 8), 'down'],
[(8, 7), 'left'],
[(7, 7), 'down'],
[(7, 6), 'left'],
Goal found; run 1 completed!
Task complete! Score: 29.667
********************************************************************************
```

I plot the run-2 path on the maze. Figure 5a and 5b are the simulation results on Maze_01; Figure 6a and 6b are the simulation results on Maze_02; Figure 7a and 7b are the simulation results on Maze_03. The scores and run-2 steps are shown in Table 2.



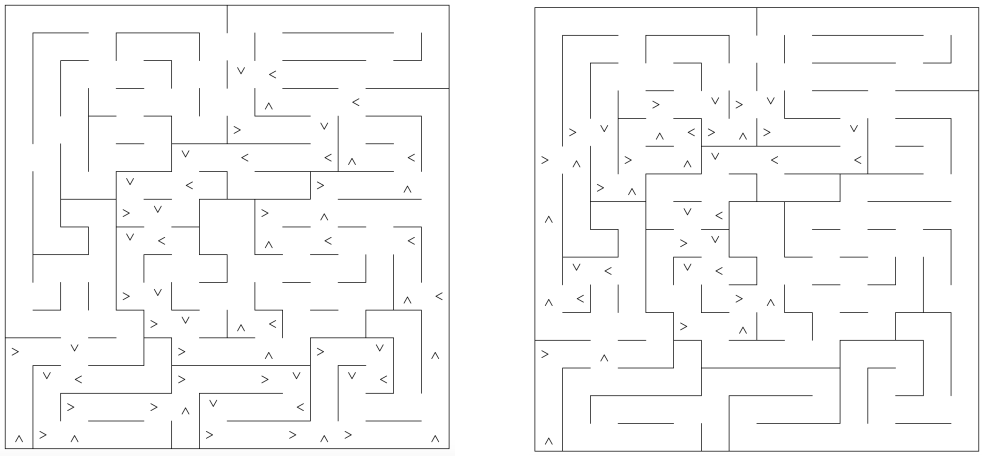
(a) Using DFS. (46 steps) (b) Using A-star. (26 steps)

Figure 5: The simulation results on Maze-01. (Run-2)



(a) Using DFS. (65 steps) (b) Using A-star. (41 steps)

Figure 6: The simulation results on Maze-02. (Run-2)



(a) Using DFS. (59 steps) (b) Using A-star. (39 steps)

Figure 7: The simulation results on Maze-03. (Run-2)

### 3.3 Refinement

I this subsection, I would like to know whether it is possible to improve the performance further by using other heuristic matrix. Notable, using other heuristic matrix sounds not make sense in general situations if we (or the robot) cannot get further information about the maze. I did this experiment just because I want to know the influences of the heuristic matrix. Let's start the experiment from Maze_01.

Let's named the previously defined heuristic matrix as $H_1$ (page 11); the all zeros heuristic matrix as $H_0$. Then,

$$H_2(i,j) = j \qquad (j = 0, 1, 2, \ldots, n-1),$$

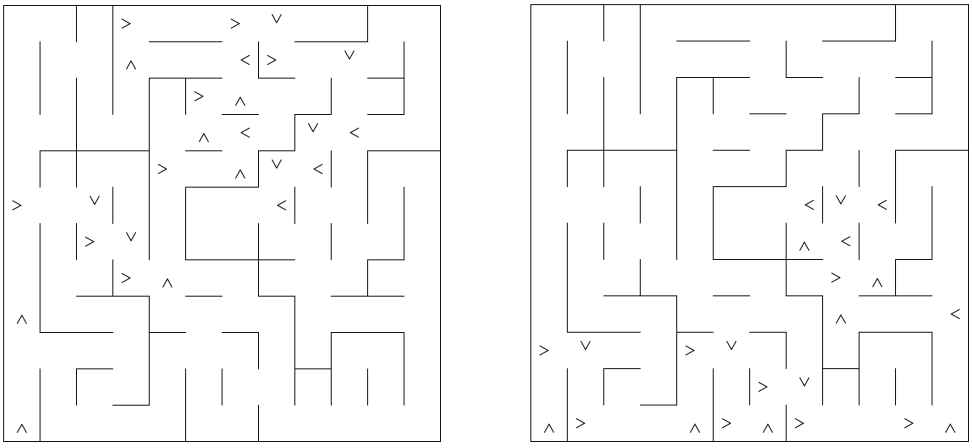
and

$$H_3(i,j) = i \qquad (i = 0, 1, 2, \ldots, n-1).$$

Using the four kinds of heuristic matrix to do simulation, the results could be obtained as shown in Table 3. In average, $H_1$ is a good design of heuristic matrix. The robot get better performance while choosing $H_2$ on Maze_01, that is because the optimal path of

Table 3: Using four kinds of heuristic matrix to do simulation on the given mazes.

| | | Maze-01 | Maze-02 | Maze-03 |
|---|---|---|---|---|
| $H_0$ | score | 49.576 | 71.233 | 73.667 |
| | run-2 steps | 46 | 65 | 59 |
| $H_1$ | score | 29.667 | 44.267 | 43.100 |
| | run-2 steps | 26 | 41 | 39 |
| $H_2$ | score | 25.233 | 63.100 | 59.167 |
| | run-2 steps | 23 | 51 | 39 |
| $H_3$ | score | 49.567 | 71.233 | 73.677 |
| | run-2 steps | 46 | 65 | 59 |



(a) Choosing $H_1$ as the heuristic matrix. (b) Choosing $H_2$ as the heuristic matrix.

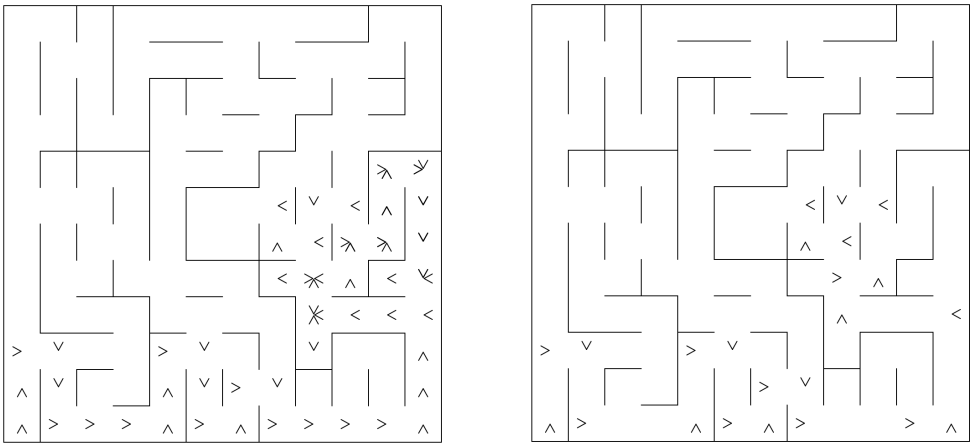
Figure 8: The run2 paths of Maze-01 while choosing different heuristic matrix.

Maze_01 is near the bottom of the Maze. Figure 8 shows the paths of Maze_01 while choosing $H_1$ and $H_2$.

From this experiment, we know that $H_1$ is a good choice in general situation. The design of heuristic matrix will influence the performance. If we know some information about the maze, we indeed can design a better heuristic matrix to obtain better performance.

# 4 Results

This section includes two subsections: *Model Evaluation and Validation* and *Justification*.



(a) (b)

Figure 9: The paths of Maze-01: (a) run1 path (66 steps); (b) run2 path (23 steps).

Table 4: A comparison with my best results and the optimal ones.

| | Maze-01 | Maze-02 | Maze-03 |
|---|---|---|---|
| My best score | 25.233 | 44.267 | 43.100 |
| My best run1 path | 66 steps | 97 steps | 122 steps |
| My best run2 path | 23 steps | 41 steps | 39 steps |
| The optimal run1 path | 30 steps | 43 steps | 49 steps |
| The optimal run2 path | 17 steps | 23 steps | 25 steps |

### 4.1 Model Evaluation and Validation

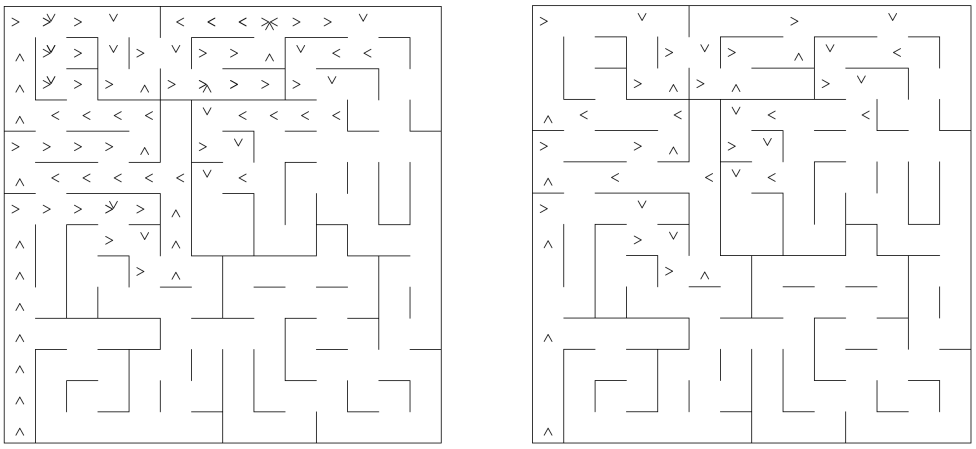
In this subsection, I will show the best paths that the robot navigating on Maze-01 to Maze-03, including run1 and run2.

For the purpose of comparison, I also show the optimal run2 paths in Figure 14.

These results are concluded in Table 4.

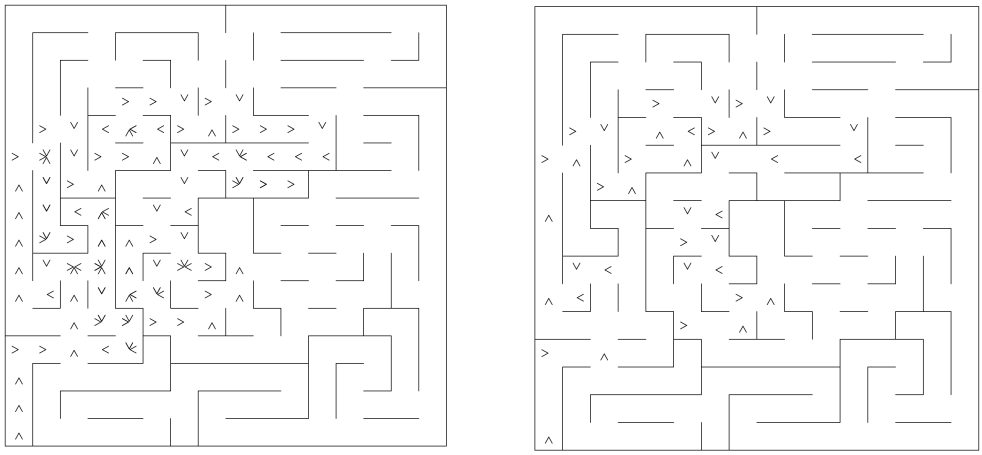
### 4.2 Justification

Based on the results mentioned in the previous subsection, we observe that the A-star search is a reasonable algorithm for path planning. Of course, my best run2 cannot achieve the performance of the optimal paths; that is because the coverage of my run1 result is not



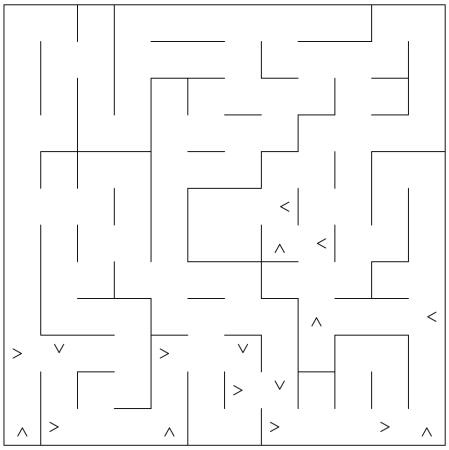
(a) (b)

Figure 10: The paths of Maze-02: (a) run1 path (97 steps); (b) run2 path (41 steps).

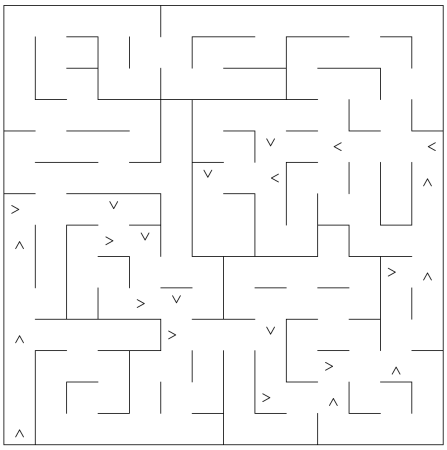


(a) (b)

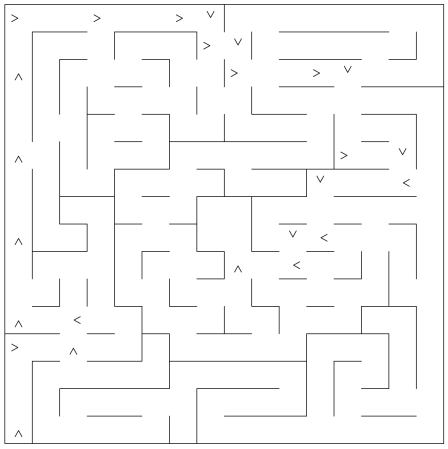
Figure 11: The paths of Maze-03: (a) run1 path (122 steps); (b) run2 path (39 steps).



(a) Maze-01 optimal run2 paths (17 steps).



(b) Maze-02 optimal run2 paths (23 steps).



(c) Maze-03 optimal run2 paths (25 steps).

Figure 12: The optimal run2 paths.

Table 5: A comparison of my best results with the benchmark.

| | Maze-01 | Maze-02 | Maze-03 |
|---|---|---|---|
| My best score | 25.233 | 44.267 | 43.100 |
| My best run1 path | 66 steps | 97 steps | 122 steps |
| My best run2 path | 23 steps | 41 steps | 39 steps |
| Coverage of my best run1 path | 31.94% | 40.82% | 30.08% |
| DFS score | 49.567 | 71.233 | 73.667 |
| DFS run1 path | 106 steps | 186 steps | 439 steps |
| DFS run2 path | 46 steps | 65 steps | 59 steps |
| Coverage of DFS run1 path | 59.72% | 63.27% | 83.98% |
| The optimal run1 path | 30 steps | 43 steps | 49 steps |
| The optimal run2 path | 17 steps | 23 steps | 25 steps |

particular high. Specifically, the coverage of run1 on maze-01 is only 31.94%; the coverage of run1 on maze-02 is 40.82%; and the coverage of run1 on maze-03 is 30.08%.

Increase the coverage of run1 path may increase the final score; this could be viewed as a kind of investment. However, my robot's attitude is conservative, so that when my robot finds the goal in first run, it immediately stops run1 navigation and begins its run2 adventure. That means, my robot does not want to invest any time in run1.

Finally, a comparison of my best results with the benchmark is shown in Table 5. We can find that DFS always uses more steps and more coverage in run1, but the investment is not effective. On the other hand, A-star adopts the distance information during the search; it makes a significant improvement than DFS.

# 5 Conclusions

Three subsections are included in this section. They are: *Free-Form Visualization*, *Reflection*, and *Improvement*.

## 5.1 Free-Form Visualization

In this subsection, I will use test_maze_01.txt as a template to design my own maze. My own maze is named test_maze_04.txt. In my maze, there is only one path from start to

goal except minor branches caused by loops. I would like to test the robustness of my robot, testing whether my robot can survived in an environment with many dead-ends. The maze designed by myself is shown in Figure 13.

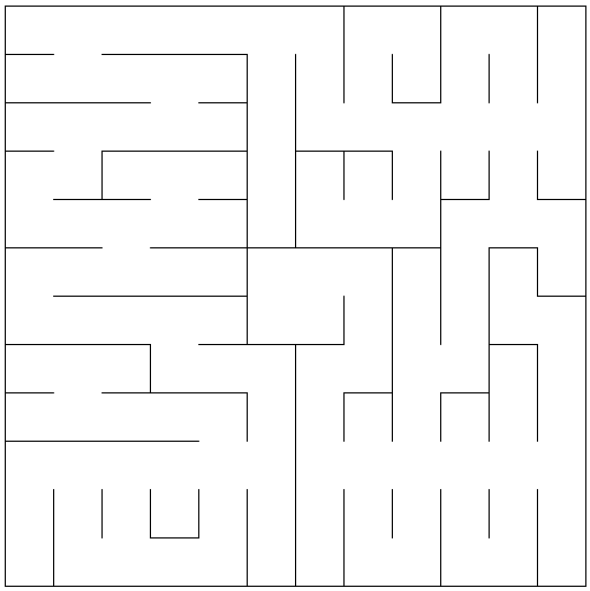
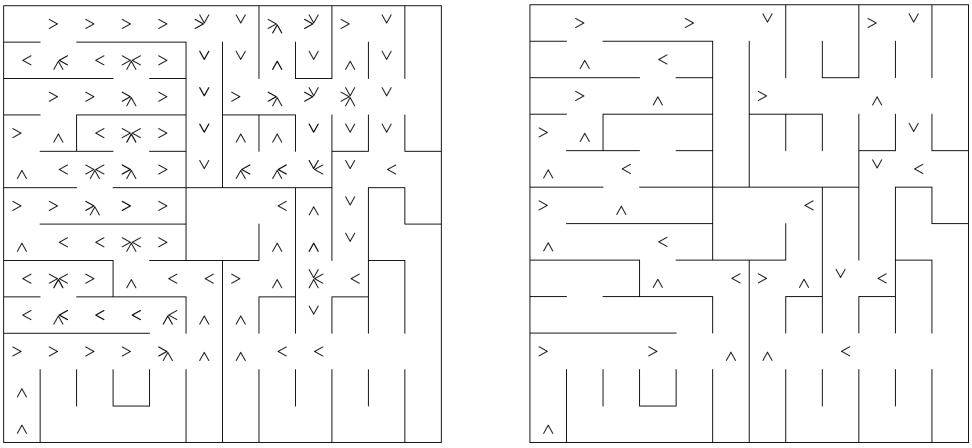


Figure 13: My own maze for testing the robustness of my robot.

There are many dead-ends, for example, locations (3,1), (0,3), (2,3), (4,8), and (7,1), etc., are cases of dead-ends. Besides, ther are also some loops, including the right-hand-side walls of (1,1) and (7,1), etc. In the simulation, I also adopt $H_1$ as the heuristic matrix, the result is shown in Figure 14.

Let's make a comparison as shown in Table 6. My run2 path has two more steps than the optimal one, because my robot wastes its time on a loop. That is, its next step follow (9,9) should be (10,9) instead of (9,11). Overall, the score of my robot on my own maze is also pretty good.



(a) The path of run1 (170 steps).

(b) The path of run2 (35 steps).

Figure 14: The simulation result on my own maze.

Table 6: A comparison with my results and the optimal ones.

| | Maze-04 |
|---|---|
| My run1 path | 170 steps |
| My run2 path | 35 steps |
| My score | 40.70 |
| The optimal run1 path | 58 steps |
| The optimal run2 path | 33 steps |
| The optimal (ideal) score | 34.93 |

### 5.2 Reflection

This project takes me over one and half a month. At first, I only implemented the DFS algorithm for my robot. I feel vary happy then, because my robot can always find the goal. However, very soon, I am not satisfied with my robot, because the score is not so good. Even though, I have spent two weeks for the results.

Then, I started to study many more, including the suggested course. I began to realize A-star maybe a good solution and began to implement A-star edition. Really, A-star search is a good choice for robot path planning problem. The only problem is the design of heuristic matrix. For some situations, we can re-design the matrix if there is *a priori* information about the structure of the maze.

In the future, I would like to design a real robot to navigate in a real maze [1].

### 5.3 Improvement

In a continuous domain, there are many issues to be considered:

- The speed needs to be controlled rather than just number of steps. Physical phenomenon should also be considered, including the momentum of the robot, the speed is not linear, etc.
- For a zigzag situation, the robot can go strait instead of make turns in the discrete counterpart.
- Real world is an uncertain environment, the readings of sensors maybe incorrect, the robot maybe "forget" its real position owing to a sliding on the road, etc. Therefore, the robot itself should perform localization for getting its real position.

In the future, I would like to design a real robot, to challenge the above-mentioned problems.

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