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HW#: 1

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#### Contents

I. Introduction	2
II. Task1: Basic A* algorithm	2
A. Model and Pseudocode	2
B. Inplementation	4
C. Result	6
III. Task2: Improved A* Algorithm	7
A. Model	7
B. Inplementation	8
C. Result and Comparison	10
IV. Task3: Path Planning for Self-driving	10
A. Model	10
B. Inplementation	11
C. Result and Comparison	12
V. Conclusion	12
VI. Acknowledgement	13
References	13

#### I. INTRODUCTION

In AI3603 class, we students have studied A\* algorithm, which can be applied to a search problem. In this homework, I try to develop a path planning framework for a service robot in the unknown environment using A\* algorithm. There are 3 tasks,

- Task1 is a naive implementation of A\* algorithm, we control the robot move forward, backward, left and right.
- Task2 is an improved inplementation of A\* algorithm, we can move upper left, upper right, bottom left, bottom right. What's more, we need to add steer cost and collision into consideration.
- Task3 is a self-driving car, I try to use Bézier curve to improve performance of Task2.

Now we are going to complete each task step by step.

#### II. TASK1: BASIC A\* ALGORITHM

#### A. Model and Pseudocode

As we learned in the class,  $A^*$  algorithm is a combination of UCS algorithm (dijkstra) (with a cost function g) and a heuristic function (h) modeling the remained cost from current position to the goal.

We model that the movement from one point to an adjacent point costs 1, since we only move the robot forward, backward, left and right in this task, we then use Manhattan distance from curret position to the goal as heuristic function.

First, I try to write down the pseudocode. I construct a data structure named node, which can represent the point at each position. See in Figure 1.

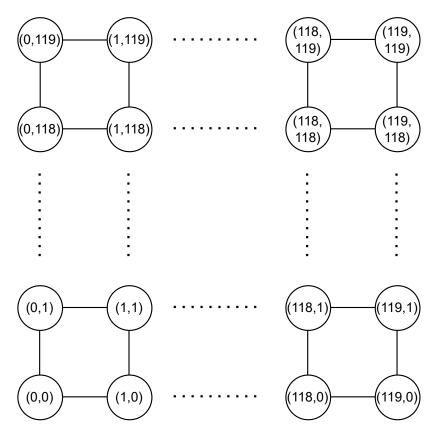


FIG. 1: Represent each point as a node.

## Algorithm 1 BasicAStarAlgorithm

Input: goal\_pos: position of goal, current\_map: current known map, current\_pos: current position.

Outcome: A path to move.

```
Outcome: A path to move.
1: initialize a 2D array distance to store the graph, we view each point on the grid as a node in the graph
2: source\_node \leftarrow the node corresponding to current\_pos
3: initialize g of source\_node as 0
4: initialize PQ \leftarrow \emptyset as a priority queue
5: add source\_node to PQ
6: while PQ is not empty do
7:
       pop current\_node out
8:
       if current\_node is in the goal area then
9:
           break
10:
       end if
       if current_node has been visited then
11:
12:
           continue
13:
       end if
                                                                             \triangleright This algorithm will be introduced later.
14:
       explore(current\_node)
15:
       Set current\_node as visited
16: end while
17: From the lastly visited node, we trace back to get the complete path from current_pos to goal_pos
18: return path
```

# Algorithm 2 explore Input: A node named node.

Outcome: Nothing. 1: get current x-axis and y-axis position 2: get x-axis and y-axis position of ancester of node3: for next\_node: each point to move (forward, backward, left, right) do if This point is out of the map then 5: break 6: end if 7: if This point is an obstacle then 8: break 9: end if 10: if  $g(node) + 1 < g(next\_node)$  then 11:  $g(next\_node) = g(node) + 1$ Set the ancester of next\_node as node 12: 13:  $PQ.push(next\_node)$ 

end if

14:

15: **end for** 

#### B. Inplementation

First, I import packages and construct data structure node. Note that I add a steer\_cost attribute to node, which can deal with the problem of too many turns easily.

```
import DR20API
     import numpy as np
import random
    from queue import PriorityQueue from matplotlib import pyplot as plt
           PriorityQueue()
     Manhattan.or.Euclidean = 1 # 1 means Manhattan and 2 means Euclidean random.seed ("AI3603")
11
     def h(pos, goal-pos):
    return np.linalg.norm(np.array(pos)-np.array(goal-pos),ord=Manhattan_or_Euclidean)
13
    class node:
    def _.init__(self, pos, goal_pos):
        self.pos = pos
        self.is_visited = False
        self.ancester = pos
        self.steer_cost = 0
        self.h_cost = h(pos, goal_pos)+random.uniform(0, 3603e-6)
        self.g_cost = MAX_G_COST
15
17
19
21
23
           def cost(self):
    return self.h_cost+self.g_cost
25
27
           def __call__(self):
                  return self.f, self.Python code
29
```

Second, the inplementation of A\* algorithm (corresponding to BasicAStarAlgorithm):

```
def A_star(current_map, current_pos, goal_pos):
    Given current map of the world, current position of the robot and the position of the goal,
    plan a path from current position to the goal using A* algorithm.

Arguments:
    current_map — A 120*120 array indicating current map, where 0 indicating traversable and 1 indicating
    obstacles.
    current_pos — A 2D vector indicating the current position of the robot.
goal_pos — A 2D vector indicating the position of the goal.

Return:
    path — A N*2 array representing the planned path by A* algorithm.

### START CODE HERE ###
global distance
distance = [[node([x,y],[100,100]) for y in range(0,120)] for x in range(0,120)]
source_node = distance[current_pos[0]][current_pos[1]]
source_node.g_cost = 0
```

```
q.put(source_node())
21
            while not q.empty():
                  le not q.empty():
current_node = q.get()[1]
if np.abs(current_node.pos[0] - goal_pos[0]) < 3 and np.abs(current_node.pos[1] - goal_pos[1]) < 3:</pre>
23
25
                         break
                  if current_node.is_visited:
27
                         continue
                  explore(current_node)
current_node.is_visited = True
29
31
            x,y = current_node.pos
           x,y = current-pos[0] and y == current-pos[1]):
    x,y = distance[x][y].ancester
33
           \begin{array}{ll} \text{path.append}\left([x,y]\right) \\ \text{path} = \text{path}\left[-3::-1\right] \text{ if } \text{len}\left(\text{path}\right) < 32 \text{ else } \text{path}\left[-3::-1\right][:32] \end{array}
35
37
           print(f"path_=_{path}")
return path
39
```

## Third, the inplementation of explore (corresponding to explore).

```
def explore(node):
    current_x, current_y = node.pos
    ances_x, ances_y = node.ancester
direc = [(0,1), (0,-1), (-1,0), (1,0)]
    for move_x, move_y in direc:
        if not (0 <= current_x+move_x <= 119 and 0 <= current_y+move_y <= 119):
            break
        if current_map[current_x+move_x][current_y+move_y]:
            break
        next_node = distance[current_x+move_x][current_y+move_y]:
        if node.g_cost + 1 < next_node.g_cost:
            next_node.g_cost = node.g_cost + 1
            next_node.steer_cost = node.g_cost + 1
            next_node.ancester = node.pos
            q.put(next_node())</pre>
```

## Forth, fill the reach\_goal function.

```
def explore(node):
    current_x, current_y = node.pos
    ances_x, ances_y = node.ancester
    direc = [(0,1), (0,-1), (-1,0), (1,0)]
    for move_x, move_y in direc:
        if not (0 <= current_x+move_x <= 119 and 0 <= current_y+move_y <= 119):</pre>
                    i\,f\ \mathtt{current\_map}\,[\,\mathtt{current\_x} + \mathtt{move\_x}\,]\,[\,\mathtt{current\_y} + \mathtt{move\_y}\,]\,:
 9
                       ext_node = distance[current_x+move_x][current_y+move_y]
                    if node.g_cost + 1 < next_node.g_cost:
    next_node.g_cost = node.g_cost + 1
    next_node.steer_cost = np.linalg.norm([current_x-ances_x-move_x,current_y-ances_y-move_y],ord=1) * 4
    next_node.ancester = node.pos
    q.put(next_node())def reach_goal(current_pos, goal_pos):
11
13
15
17
            Given current position of the robot, check whether the robot has reached the goal
19
            current_pos — A 2D vector indicating the current position of the robot. goal_pos — A 2D vector indicating the position of the goal.
21
23
            is reached — A bool variable indicating whether the robot has reached the goal, where True indicating reached n^{nn}
25
27
               ## START CODE HERE ###
29
            if np.abs(current_pos[0] - goal_pos[0]) < 20 and np.abs(current_pos[1] - goal_pos[1]) < 20:
                    return True
31
            return False
### END CODE HERE ###
return is_reached
```

## Lastly, add some code to main and plot the trace of robot.

```
if __name__ == '__main__':
    # Define goal position of the exploration, shown as the gray block in the scene.
    goal.pos = [100, 100]
    controller = DR20API.Controller()

# Initialize the position of the robot and the map of the world.
    current.pos = controller.get_robot_pos()

print(f"current.pos_=_(current.pos}")
    current.map = controller.update_map()

total.path = []
# Plan-Move-Perceive-Update-Replan loop until the robot reaches the goal.

while not reach_goal(current.pos, goal.pos):
    # Plan a path based on current map from current position of the robot to the goal.

while not reach_goal(current.map, current.pos, goal.pos)
    total.path.extend(path[0:len(path)-3])

# Move the robot along the path to a certain distance.
    controller.move_robot(path)
# Get current_pos = controller.get_robot_pos()
```

```
print(f"current-pos_=={current-pos}")
# Update the map based on the current
current_map = controller.update_map()
20
                                                                                                                                        information of laser scanner and get the updated map
22
                   # Plot and Stop the simulation
controller.stop_simulation()
24
26
                    obstacles_x , obstacles_y = [] , []
                  obstacles_x , obstacles_y - 1, , , ,
for i in range(120):
    for j in range(120):
        if current.map[i][j] == 1:
            obstacles_x.append(i)
            obstacles_y.append(j)
28
30
32
                   path.x , path.y = [] , []
for path.node in total.path:
    path.x .append(path.node[0])
    path.y .append(path.node[1])
34
36
                  plt.plot(path_x, path_y, "-r")
plt.plot(current_pos[0], current_pos[1], "xr")
plt.plot(goal_pos[0], goal_pos[1], "xb")
plt.plot(obstacles_x, obstacles_y, ".k")
plt.grid(True)
plt.axis("equal")
plt.savefig("task1.pdf")
38
40
42
44
```

#### C. Result

If we run the code without add steer\_cost in f = g + h, i.e. we write node.\_\_call\_\_ function as follows:

```
def __call__(self):
    self.f = self.h_cost+self.g_cost # no self.steer_cost
    return self.f, selfPython code
```

After run the code, I get the trace of robot as shown in Figure 2. We can see that there are too many turns, which will cause much time waste.

After adding steer cost, we can see that the trace of robot is much more straight then that before, shown in Figure 3.

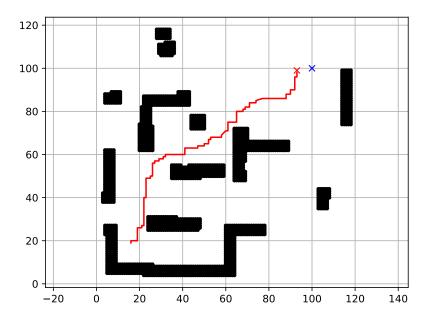


FIG. 2: The trace of robot in Task1 without steer cost.

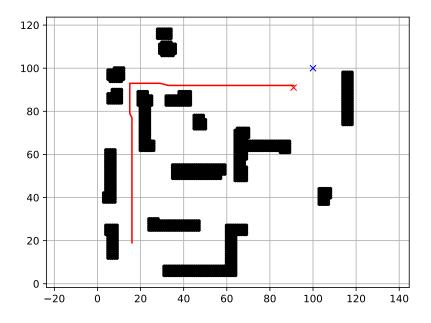


FIG. 3: The trace of robot in Task1 after applying steer cost.

#### III. TASK2: IMPROVED A\* ALGORITHM

#### A. Model

In Task2, we want to improve the performance of A\* planner written in Task1. Specifically, I will do that in three perspective:

- Add four more directions into consideration (upper left, upper right, bottom left, bottom right).
- Add a penalty term when there are some obstacles along each direction.
- Add a penalty term for steering in each position.

First, we need to add four more directions in explore function. As we model the cost from one point to its adjacent point to be 1, the cost for this four new movement should be  $\sqrt{2}$ . It's reasonable since the amount of fuel can be considered decreasing linearly with the distance moved.

What's more, since now we can move with a line to the goal with an angle of  $45^{\circ}$ , we can not use Manhattan distance as heuristic function any more, since h may be **larger than**  $h^*$  in some point, which will lead to wrong choice of path. So we use **Euclidean distance** instead ( $\ell_2$ -norm). Euclidean distance can always be smaller than  $h^*$  since the shortest distance from current position to goal is a straight line between them, so this choice makes sense.

Second, I add an obstc\_cost in node, which calculate the number of obstacles in a direction. As shown in Figure 4, I sum over a 5\*5 area for each direction (Blue boxes represent current\_node, gray boxes represent obstacles. There are 8 types of relationships between 5\*5 summing area and current\_node).

Third, I use the relationship between current\_node and its ancester node with direction, to calculate the steer cost. Since it's nearly impossible to move back to former position, we just use  $\ell_1$ -norm to calculate how many 45° to turn. An example is shown in Figure 5. The position is relative to current\_node. The

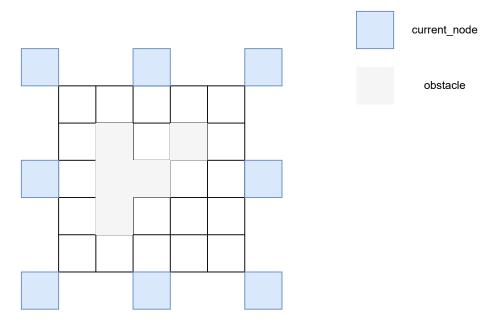


FIG. 4: Calculate penalty term for obstacles.

steer angle

$$\theta = \{ | (next\_node.x - current\_node.x) - (current\_node.x - ancester\_node.x) | \\ + | (next\_node.y - current\_node.y) - (current\_node.y - ancester\_node.y) | \} * 45^{\circ}$$

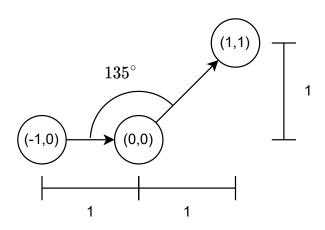


FIG. 5: An example to calculate steer angle.

## B. Inplementation

First, I modify the definition of node, change heuristic function to be Euclidean, add a function named obstacle\_cost to calculate penalty term of collision.

```
MAX.G.COST = 1e3
q = PriorityQueue()
Manhattan.or.Euclidean = 2 # 1 means Manhattan and 2 means Euclidean
random.seed("A13603")
def h(pos, goal_pos):
    return np.linalg.norm(np.array(pos)-np.array(goal_pos),ord=Manhattan_or_Euclidean)
def het cales cost(current man_current nos_direc).
     def obstacles_cost(current_map, current_pos, direc)
             Given current map of the world, direction of the robot, calculate the obstacles cost for each of 8 directions.
11
                                      - A 120st120 array indicating current map, where 0 indicating traversable and 1 indicating
                      obstacles.
             current_pos — A 2D vector indicating the current position of the robot. direc — A 2*1 array indicationg the pos after one of [U,UR,R,DR,D,DL,L,UL] movement.
13
15
             Returns
17
             A double
19
             distance = 3
            width = 5
left_right = direc[0]
up_down = direc[1]
center = [current_pos[0] + distance*left_right , current_pos[1] + distance*up_down]
return 1/32*np.sum(current_map[center[0] - width:center[0] + width+1,center[1] - width:center[1] + width+1])
21
23
    class node:
    def __init__(self, pos, goal_pos):
        self.pos = pos
        self.is_visited = False
        self.ancester = pos
        self.h_cost = h(pos, goal_pos)+random.uniform(0, 3603e-6)
        self.g_cost = MAX_G_COST
25
27
29
31
33
             def cost(self):
    return self.h_cost+self.g_cost
35
             def --call--(self):
    self.f = self.h_cost+self.g_cost
    return self.f, self
37
39
```

#### Second, I modify A\* algorithm.

```
def Improved_A_star(current_map, current_pos, goal_pos):
           Given current map of the world, current position of the robot and the position of the goal, plan a path from current position to the goal using improved A\ast algorithm.
 3
           current_map — A 120*120 array indicating current map, where 0 indicating obstacles.
current_pos — A 2D vector indicating the current position of the robot.
goal_pos — A 2D vector indicating the position of the goal.
                                  - A 120st120 array indicating current map, where 0 indicating traversable and 1 indicating
11
           Return: path — A N*2 array representing the planned path by improved A* algorithm.""
13
15
           ### START CODE HERE ###
           ### START CODE HERE ### global distance distance = [[node([x,y],[100,100]) \text{ for } y \text{ in } range(0,120)] \text{ for } x \text{ in } range(0,120)] source_node = distance [current_pos[0]][current_pos[1]] source_node.g_cost = 0 q.put(source_node())
17
19
21
           23
25
                  if current_node.is_visited:
                  continue
explore (current_node)
27
29
                  current_node.is_visited = True
           x,y = current_node.pos
path = [[x,y]]
while x != current_pos[0] or y != current_pos[1]:
    x,y = distance[x][y].ancester
    path.append([x,y])
path = path[-3::-1] if len(path) < 22 else path[-3::-1][:22]</pre>
31
33
35
           path = path[-3::-1] if

print(f"path == {path}")

### END CODE HERE ###

return path
37
```

## Third, I modify explore function.

```
def explore(node):
    current_x, current_y = node.pos
    ances_x, ances_y = node.ancester
    direc = [(0,1),(1,1),(1,0),(1,-1),(0,-1),(-1,-1),(-1,0),(-1,1)]

for i,(move_x, move_y) in enumerate(direc):
    if not (0 <= current_x+move_x <= 119 and 0 <= current_y+move_y <= 119):
        break
    if current_map[current_x+move_x][current_y+move_y]:
        break
        next_node = distance[current_x+move_x][current_y+move_y]

steer_cost = np.linalg.norm([current_x-ances_x-move_x, current_y-ances_y-move_y],ord=1) * 4

obstc_cost = obstacles_cost(current_map, node.pos, direc[i])</pre>
```

```
if i % 2 == 0:
    if node.g_cost + 1 + steer_cost + obstc_cost < next_node.g_cost:
        next_node.g_cost = node.g_cost + 1 + steer_cost + obstc_cost
        next_node.ancester = node.pos
        q.put(next_node())

else:
    if node.g_cost + np.sqrt(2) + steer_cost + obstc_cost < next_node.g_cost:
        next_node.g_cost = node.g_cost + np.sqrt(2) + steer_cost + obstc_cost
        next_node.ancester = node.pos
    q.put(next_node())</pre>
```

Other codes nearly remain the same as Task1.

#### C. Result and Comparison

In Task2, I got a much better result than Task1 shown in Figure 6. Here are some comparisons.

- The computational time of Task2 is larger than Task1. However, since this map is not very large, the increase of time is acceptable.
- The possibility of collision is reduced (although Figure 6 seems to have some collisions, they are mainly due to plot function), in most cases, robot is more away from obstacles.
- The path in Task2 is more close to optimal path, since the total distance or time is lower than Task1.

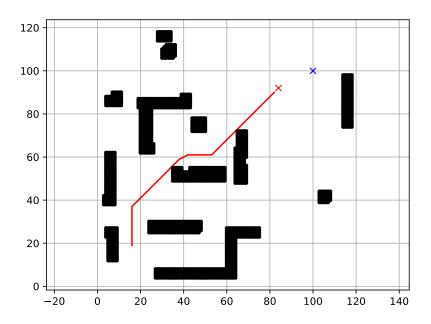


FIG. 6: The trace of robot in Task2.

#### IV. TASK3: PATH PLANNING FOR SELF-DRIVING

#### A. Model

In this Task, I modify my code from Task2, and use **Bézier curve** to improve performance, and get a smoother path.

As we know, Bézier curve is widely used in computer science, here is an introduction to it's application in robotics [1].

Bézier curves can be used in robotics to produce trajectories of an end-effector due to the virtue of the control polygon's ability to give a clear indication of whether the path is colliding with any nearby obstacle or object. Furthermore, joint space trajectories can be accurately differentiated using Bézier curves. Consequently, the derivatives of joint space trajectories are used in the calculation of the dynamics and control effort (torque profiles) of the robotic manipulator.

Here is an example [1].

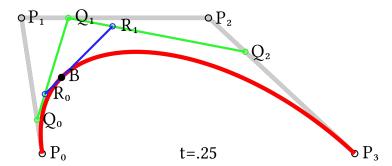


FIG. 7: An example of Bézier curve [1]

#### B. Inplementation

We need to modify the Improved\_A\_Star function to get a new function planner.

```
\mathbf{def} \ \ \mathtt{planner} \, (\, \mathtt{current\_map} \, \, , \ \ \mathtt{current\_pos} \, \, , \ \ \mathtt{goal\_pos} \, ) :
            Given current map of the world, current position of the robot and the position of the goal, plan a path from current position to the goal using improved A* algorithm.
                                    - A 120*120 array indicating current map, where 0 indicating traversable and 1 indicating
            current_map
            obstacles.

current_pos — A 2D vector indicating the current position of the robot.

goal_pos — A 2D vector indicating the position of the goal.
            Return: path — A N*2 array representing the planned path by improved A* algorithm """
11
13
15
            ### START CODE HERE ###
           ### START CODE HERE ###
global distance
global distance
distance = [[node([x,y],[100,100]) for y in range(0,120)] for x in range(0,120)]
source_node = distance[current_pos[0]][current_pos[1]]
source_node.g_cost = 0
q.put(source_node())
17
19
21
            while not q.empty():
                   if np.abs(current_node = q.get()[1] if np.abs(current_node.pos[0] - goal_pos[0]) < 3 and np.abs(current_node.pos[1] - goal_pos[1]) < 3:
23
25
                           break
                   if current_node.is_visited:
                   continue
explore(current_node)
current_node.is_visited = True
27
29
31
                 = current_node.pos
            x,y = current.node.pos
path = [[x,y]]
while x != current_pos[0] or y != current_pos[1]:
    x,y = distance[x][y].ancester
    path.append([x,y])
path = path[-3::-1] if len(path) < 22 else path[-3::-1][:22]
path = np.array(path)</pre>
33
35
37
            def bernstein_poly(n, i, t):

return scipy.special.comb(n, i) * t ** i * (1 - t) ** (n - i)
39
41
            def bezier(t, control-points):
    n = len(control-points) - 1
    return np.sum([bernstein-poly(n, i, t) * control-points[i] for i in range(n + 1)], axis=0)
43
45
            traj = []
n_points = 220
```

## C. Result and Comparison

Now the path from start to goal is shown in Figure 8. The most progress of this task is the smoothness. We avoid sharp turn in this task, which can make the speed retain and have more flexibility to avoid collision.

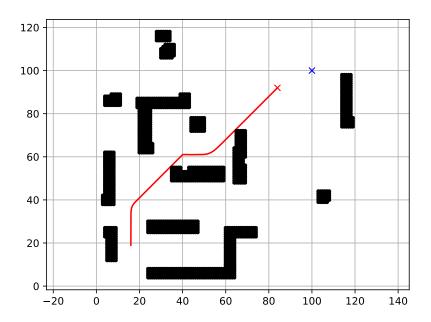


FIG. 8: The trace of robot in Task3

#### V. CONCLUSION

In this homework, I combine the knowledge from the class and Python code, and build a self-driving car in virtual world. From this homework, I not only learn how to apply AI to a real task, but I get into know how to do optimization, how to analyze, how to model, those are things required for researching.

## VI. ACKNOWLEDGEMENT

I thank fo	or Cheng	Lei,	since he	e commi	$_{ m inicate}$	with	me	and	share	me	some	good	and	useful	inspir	ations
(No code).																

 $[1] \ \mathtt{https://en.wikipedia.org/wiki/B\%C3\%A9zier\_curve}$