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Algorithamic Motion Planning

HW-3

Q.1

Ans a) A planning algorithm is called a "complete" planning algorithm if it can find a path from start configuration to the goal configuration if such a path exists in finite time or responds with a failure condition in case of infeasibility of a path.

b) A planning algorithm is called an optimal, in the sense that ~~is~~ given a cost function $c: \Gamma \to \mathbb{R}^{\geq 0}$, it can find a path $\gamma^*: [0,1] \to Q_{free}$ such that

$$\gamma^* = \underset{\gamma \in \Gamma}{\arg\min} \{ c(\gamma(t)) \mid \gamma(0) = q_{start} \;\&\; \gamma(1) = q_{goal} \}$$

c)

Ans In terms of completeness the alg wavefront planner will find a path from the goal to the start if such a path exists. This assumes the fact that the obstacles, start & goal are not dynamic and & poses of all obstacles are known. And thus it is a complete algo

In sense of optimality, the wavefront planner is optimal in the sense of grid world (discritigation) and could be sub-optimal in the continious domain. It is a kind of BFS (Breadth first search) assiging and manipulating weights along the search.

~~A~~ Wavefront algorithm satisfies the 3 conditions ~~to~~

1) It provides a stage index indicating current plan step
2) It moves over a cost function to ~~ai~~ optimize current stage index
3) It consists of a termination condition /action when it is time to stop the plan & fin the cost

Q.2

a) (i) Attached as a color pdf quiver plot. ~~at the~~

(ii) The parameters ~~selecte~~ ~~were~~ selected were

DSTAR = 8

ξ, Attraction Gain = 10

η, Repulsive Gain = 100

$Q^* = [1, 2]$

Since the start was closer to ~~a~~ the 1^{st} obstacle, a large repulsive gain ~~he~~ had to chosen with varying Q^* start values to account for the path generated to follow in between the obstacles

Additionally, to prevent excess quadratic flow of attraction potential, ~~a~~ d^* was selected to be 8 units.

iv) length of the path generated = 6.14 units

iii) Path generated and vector field have been combined in the same plot.

v) Absolutely NOT, for different values of d^* & Q_i^* different path length are generated.

b)

Ans $\boxed{\text{For Workspace - 1}}$

The following parameters were selected

$d^* = 3$

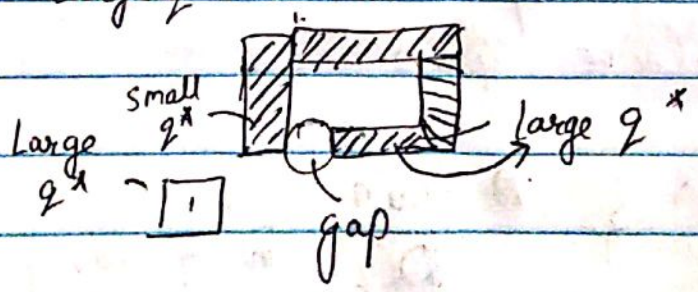
ζ = Attraction Gain = 9.2

η = Repulsive Gain = 2

$Q^* = [2.7, 0.5, 1.2, 1.2, 5]$

(i) d^* was chosen closer to goal to get quadratic convergence away from the goal, but this did not significantly affect the result

For obstacles closer to start large Q^* had to be chosen, to prevent local minimas, and for the small gap, one obstacle was given a large q^*



(ii) Attached

(iii) length of the path generated = 8.31 units

(iv) Absolutely NOT, different path lengths are generated for different values

For Workspace 2

Classic Gradient Descent approach was unable to find path and was regularly getting stuck on the local minima,

Additional Repulsive Potential function along with the original Potential fields had to be used to create a elliptical potential fields around the obstacles.

The base for these additional function was considered as a distance of the center of the obstacles from the current state of the robot and was used as an additional repulsive heuristic adding to the repulsive Gain

i.e,

$$U'_{rep}(q) \begin{cases} \dfrac{\text{Gain}}{\left(D(q - \text{center of gravity of the obstacle}\right)^2} & \text{if } D(q) \leq r \\ 0 & \text{if } D(q) > r \end{cases}$$

Using the additional heuristic as explained above ~~gave~~ leads to following parameters

$\eta = [4, 4, 7, 7, 7, 7, 7, 7, 7]$

$\sigma^* = [4, 4, 6, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1]$

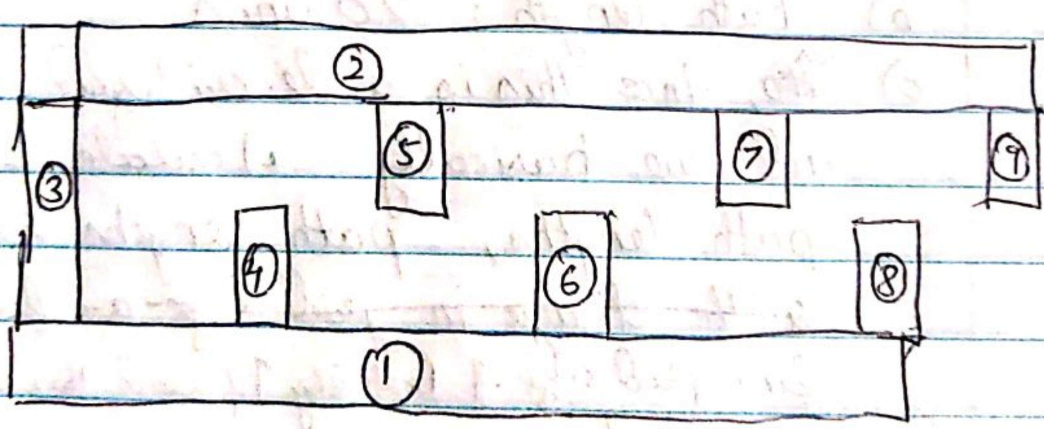
Centroid Gain = [40, 60, 20, 50, 50, 50, 50, 50, 50]

Obs Radius = [5, 5, 7.5, 3.5, 3.5, 3.5, 3.5, 3.5, 3.5]

Each element of the above parameters ~~are~~ represent the parameters for the obstacles, i.e, the 1st element of η, σ^*, Centroid Gain, Obstacle Radius are used for the 1st obstacle,

Namely

Obstacle Index



(ii) Path length generated : Attached

~~(iii)~~ (iii) Lengths of the path generated : 64.32 units

(iv) Absolutely NOT, I was not able to get the gradient descent to converge with classic potential fields and had to use additional heuristics, thus changing d^{*} & Q_i leads to different path length.

0.3

Ans $\boxed{\text{Workspace - 1}}$

a) Attached

b) Path length : 20 units

c) Yes ~~No~~, since this is a distritized ~~world~~ space, and we basically calculate L1 norm as path lengths, path lengths ~~remain the same with change in grid size~~ are found to change for very fine grid size. ~~I Probably~~ I found this to happen for grid size of 0.05 and less

$\boxed{\text{Workspace - 2}}$

a) Attached

b) Path length : 44 units

c) Path lengths, are found to change ~~remain~~ the ~~same~~ ~~irrespective~~ of grid size because of L1 norm used for path length calculation and very fine grid size causes the change in results, I found that results change for grid size less than 0.05 units and less

Scanned with CamScanner

Q.3 Q) The wavefront planner does a better job navigating along the obstacles to reach goal when in comparison with gradient descent.

Q.4

Ans Attached