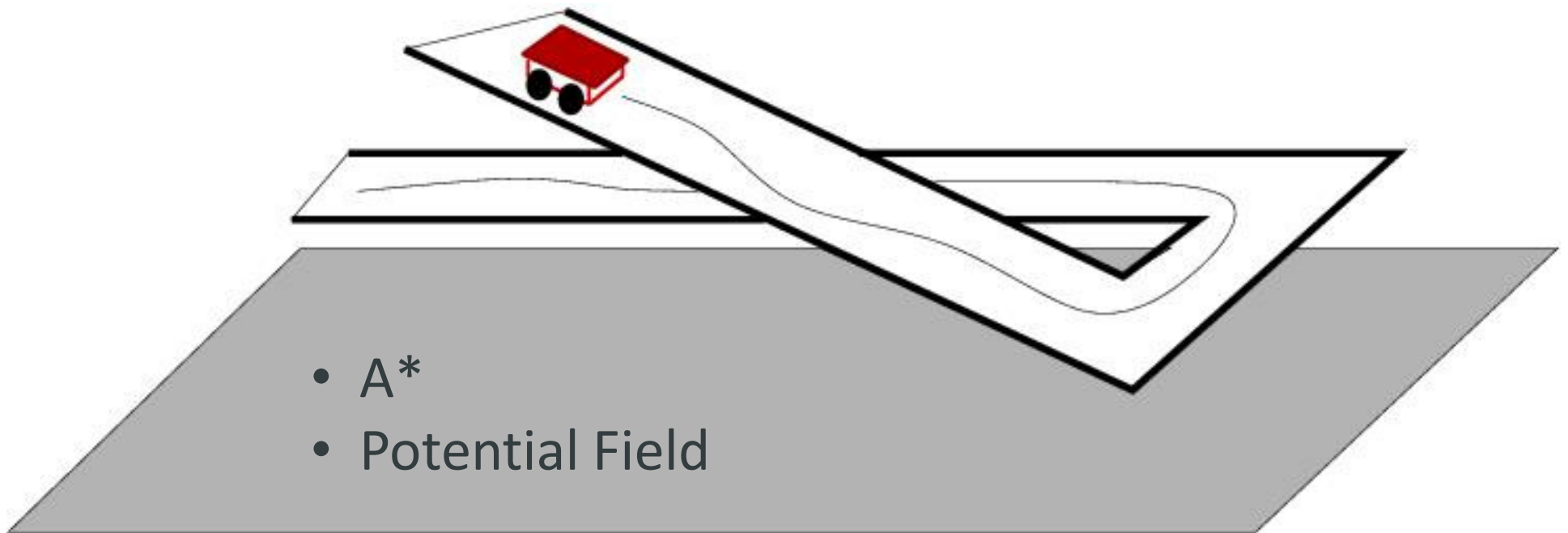


Lecture 8: ROBOT PATH PLANNING



Robot Path Planning

GOALS

- collision-free trajectories
- robot should reach the goal location as fast as possible

requires an algorithm to find a suitable path between a start and target point whilst avoiding certain areas referred to as obstacles.

Path planning algorithm - A*

- presented in 1968 by Hart *et al.*
- is admissible, i.e. guarantees to find the **shortest path**, if there is one
- is minimalistic, i.e. if compared to other admissible algorithms with the same knowledge of the search area, it will investigate the minimal amount of nodes necessary to find an **optimal** path.

The A* Search

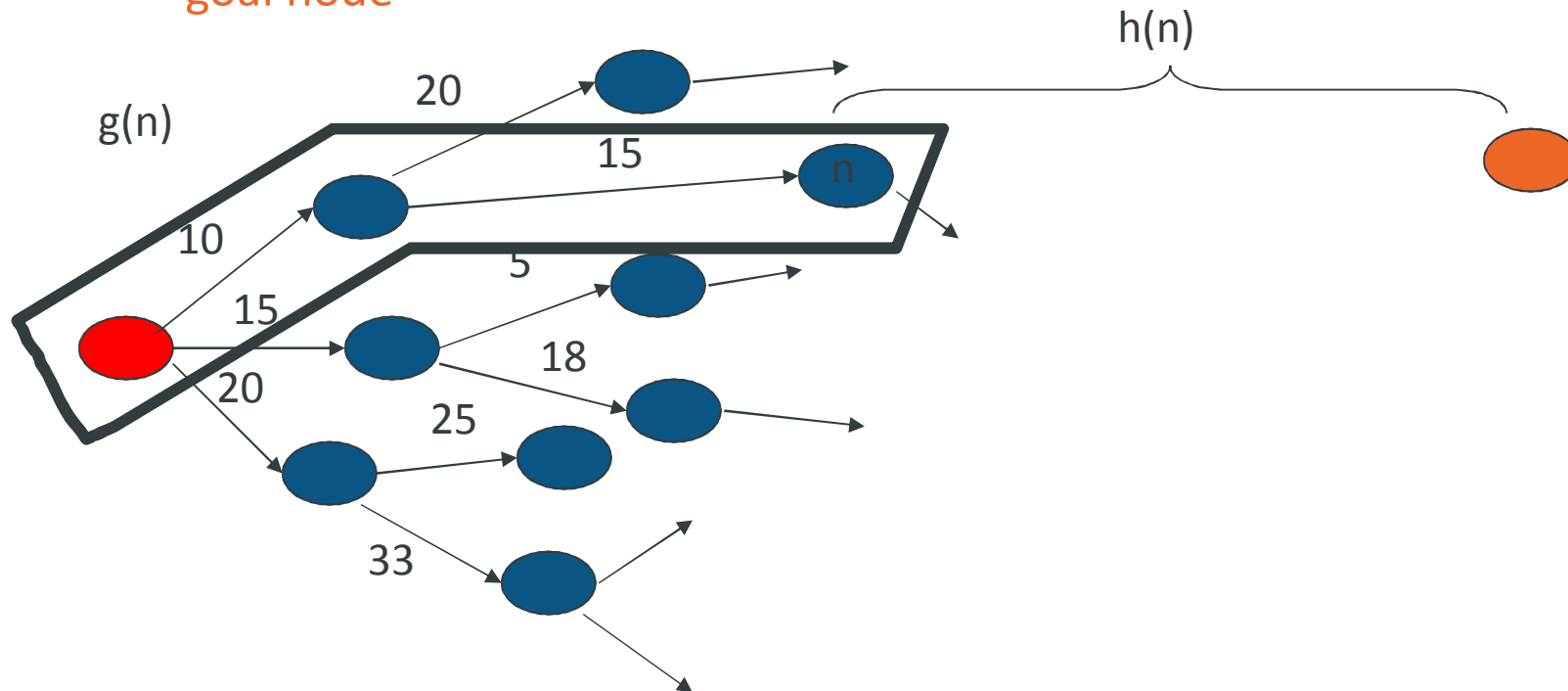
- A* is an algorithm that:
 - Uses heuristic to guide search
 - While ensuring that it will compute a path with minimum cost

- A* computes the function $f(n) = g(n) + h(n)$
 - “actual cost” (pointing to $g(n)$)
 - “estimated cost” (pointing to $h(n)$)

- $g(n)$: cost of moving from the starting point to the node n
- $h(n)$: is an estimate of the cost of the distance between the node n and the goal point

The A* Search

- $f(n) = g(n) + h(n)$
 - $g(n)$ = “cost from **the starting node** to reach n ”
 - $h(n)$ = “estimate of the cost of the cheapest path from n to the **goal node**”



Heuristics

- technique designed for solving problem **quickly** when classic methods are too slow, or **finding an approximate solution** when classic methods fail to find an exact solution. It can be considered a shortcut.
- in A* to be admissible, the heuristic may never **overestimate** the cost of the optimal path from node n to the target node:

$$h(n) \leq \hat{h}(n) \text{ for all } n$$

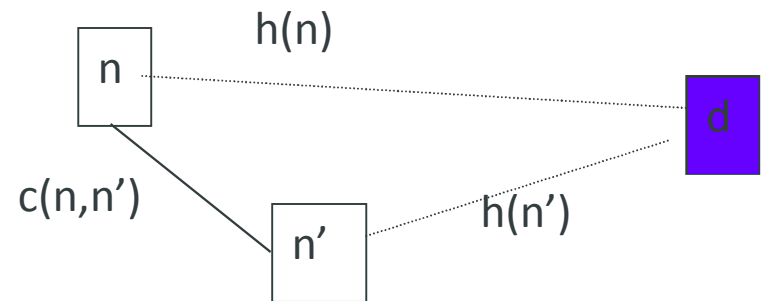
where $h(n)$ is some estimate for the cost of the optimal path from node n to the target node and $\hat{h}(n)$ is the actual cost.

Heuristics (cont.)

- A* generates an optimal solution if $h(n)$ is an admissible heuristic and the search space is a tree:
 - $h(n)$ is **admissible** if it never overestimates the cost to reach the destination node
- A* generates an optimal solution if $h(n)$ is a consistent heuristic and the search space is a graph:
 - $h(n)$ is **consistent** if for every node n and for every successor node n' of n :

$$h(n) \leq c(n, n') + h(n')$$

- If $h(n)$ is consistent then $h(n)$ is admissible
- Frequently when $h(n)$ is admissible, it is also consistent



Path planning algorithm – A* implementation

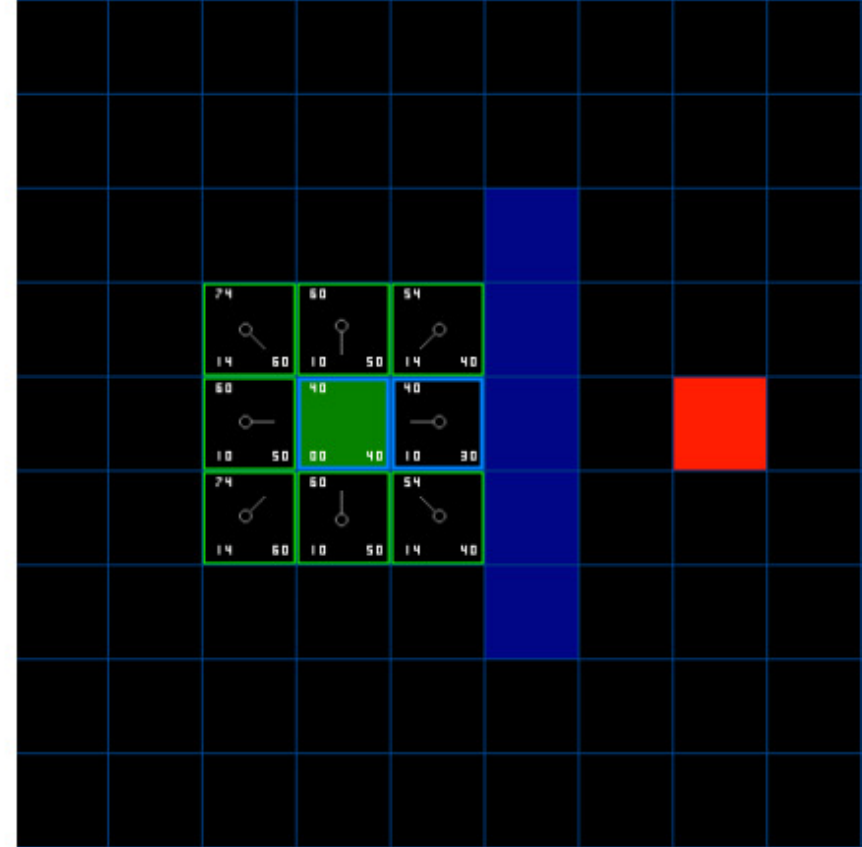
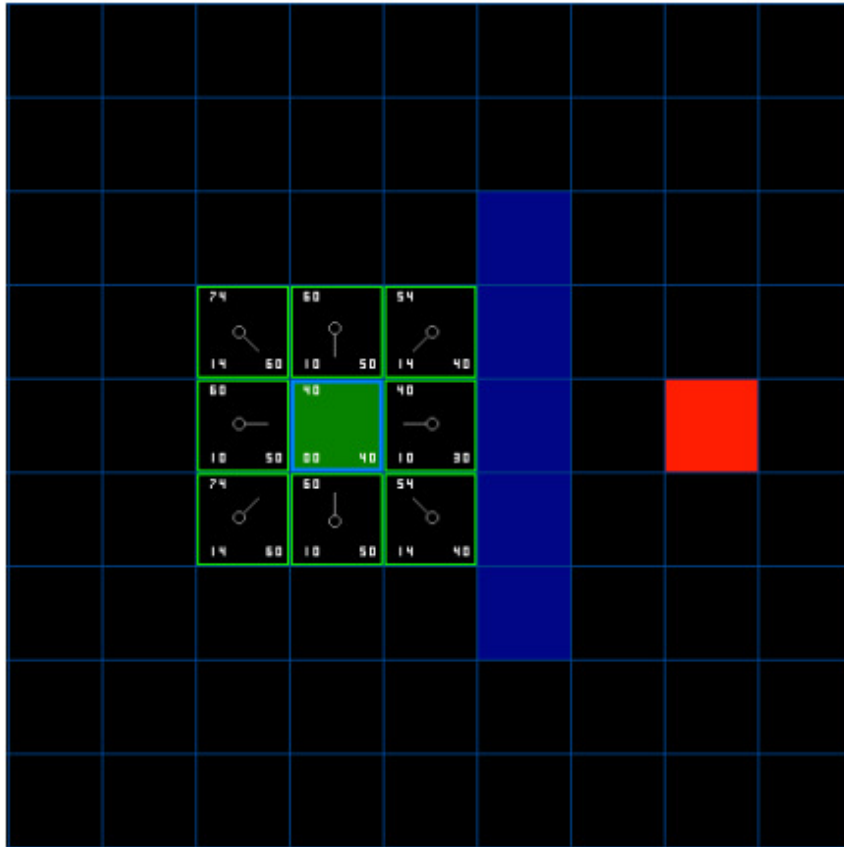
Variables and functions:

- n : node in the search space
- *close list*: contains all the nodes that have already been explored and the obstacles(added before starting the search)
- *open list*: contains all the nodes that still need to be checked
- $f(n)=g(n)+h(n)$

Path planning algorithm – A* implementation(cont.)

1. Set start node as current node and add it to the *closed list*
2. add all neighbours of the current node to *open list* along with $g(n)$, $h(n)$, $f(n)$ and their parent node
3. if a neighbour is already in the open list, check if the $f(n)$ score is lower and if so, update $g(n)$, $h(n)$, $f(n)$ and its parent
4. choose the node with the smallest $f(n)$ score in the *open list*, set it as the current node, remove it from the *open list* and add it to the *closed list*
5. repeat step 2 through 4, until the target node is added to the *closed list*, or until the *open list* is empty
6. if the target node is found, retrace the nodes by identifying their parents until the start node is found; this is the shortest path
7. if the *open list* is empty, no path to the target is possible

Path planning algorithm – A* implementation



Heuristics(cont.)

MANHATTAN

$$h(n) = |x_n - x_{goal}| + |y_n - y_{goal}|$$

x_n, x_{goal}, y_n and y_{goal} are the node x-position, goal x-position, node y-position and goal y-position.

DIAGONAL

$$h_{manhattan}(n) = |x_n - x_{goal}| + |y_n - y_{goal}|$$

$$h_{diagonal}(n) = \min(|x_n - x_{goal}|, |y_n - y_{goal}|)$$

$$h(n) = \sqrt{2} h_{diagonal}(n) + (h_{manhattan}(n) - 2 h_{diagonal}(n))$$

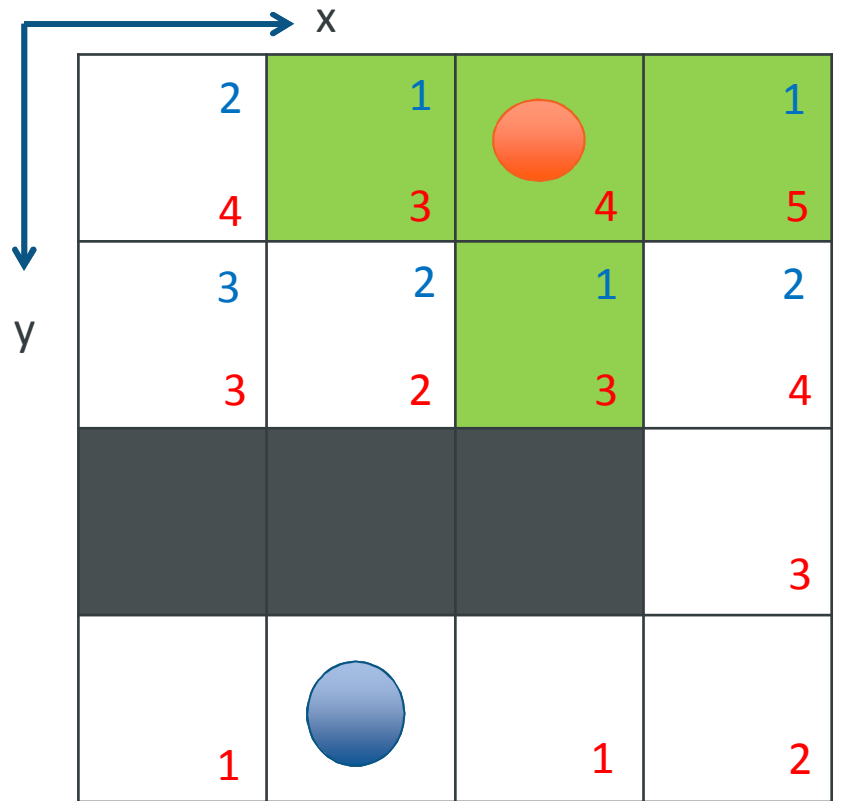
Heuristics(cont.)

EUCLIDIAN

$$h(n) = \sqrt{(x_n - x_{\text{goal}})^2 + (y_n - y_{\text{goal}})^2}$$

Square root is relatively computational complex

A*- Path Planning



(2,4)

$H(n)$ $g(n)=1$

Close list

(1,3)
(2,3)
(3,3)
(3,1)

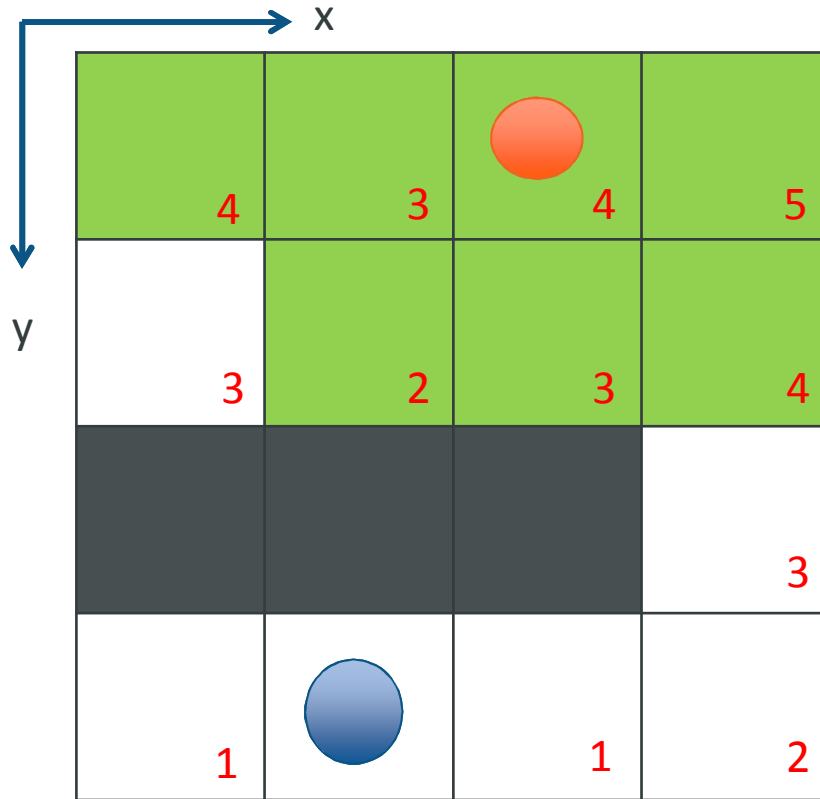
Starting node

(3,1)

Open list

(2,1)=4 (4,1)=6 (3,2)=4

A*- Path Planning



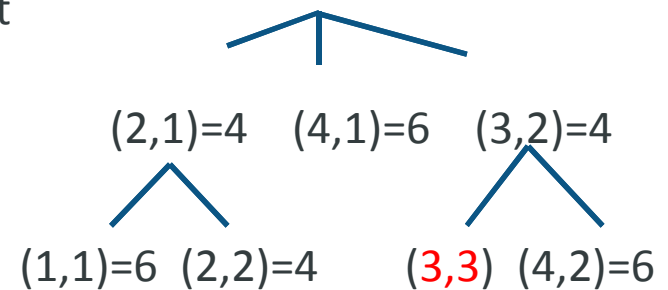
(2,4) $H(n)$ (Manhattan) $g(n)=1$

Close list

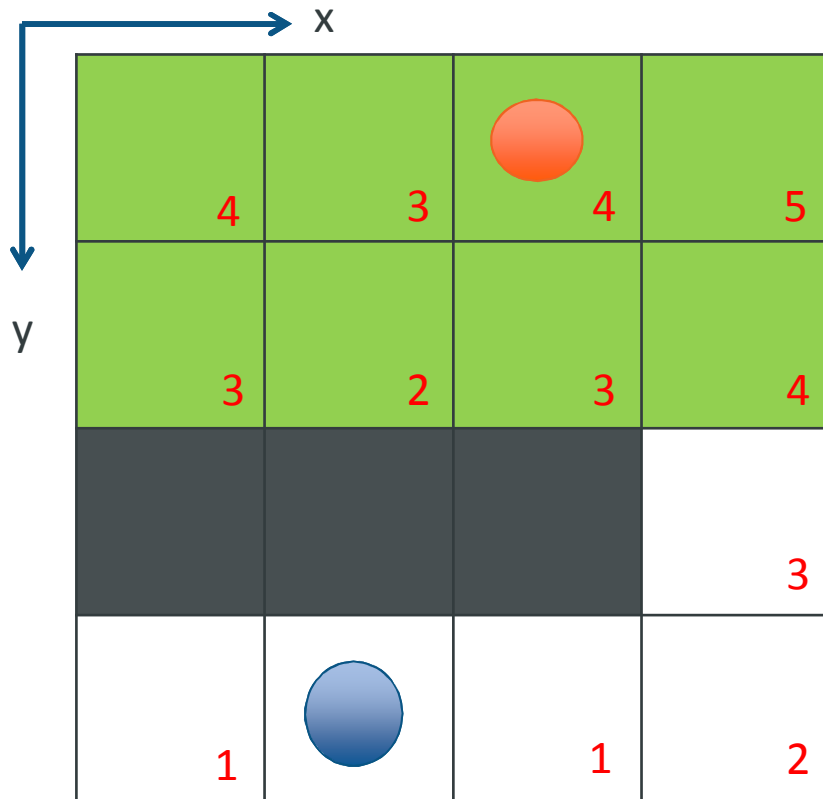
(1,3)
(2,3)
(3,3)
(3,1)
(2,1)
(3,2)

Starting node

(3,1)



A*- Path Planning



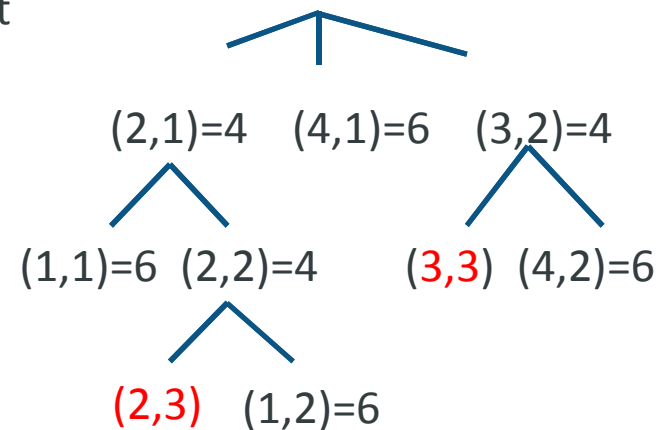
(2,4) $H(n)$ (Manhattan) $g(n)=1$

Close list

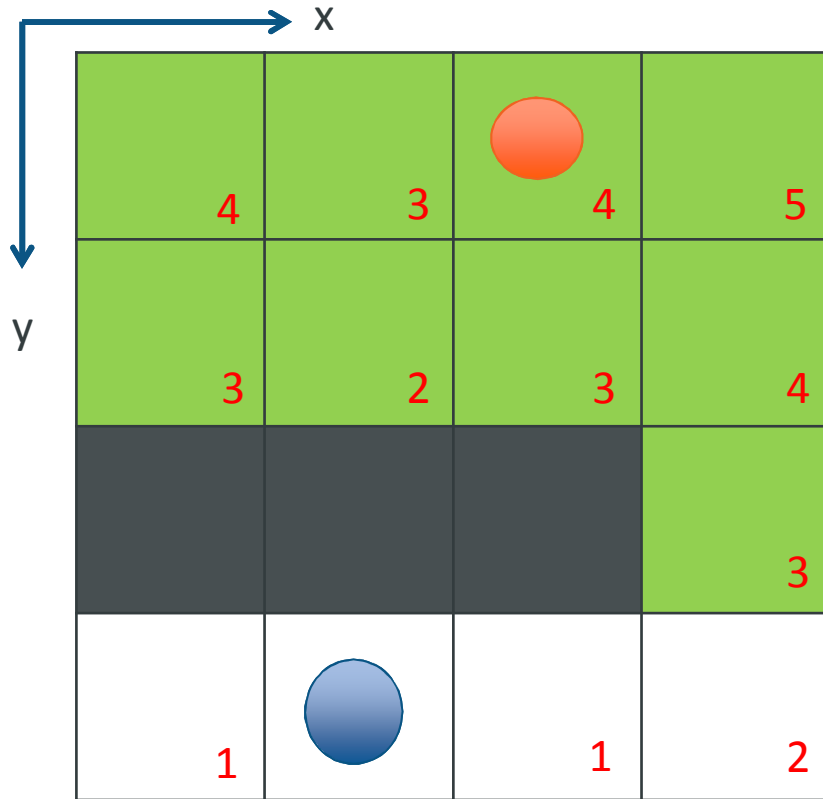
(1,3)
(2,3)
(3,3)
(3,1)
(2,1)
(3,2)
(2,2)

Starting node

(3,1)



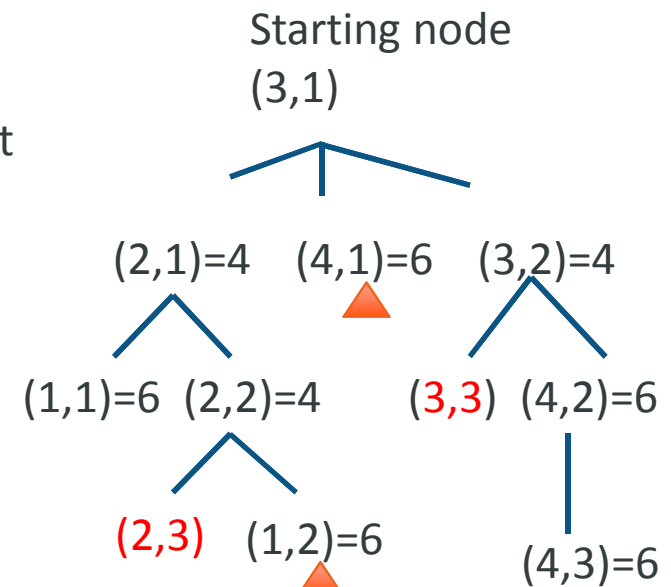
A*- Path Planning



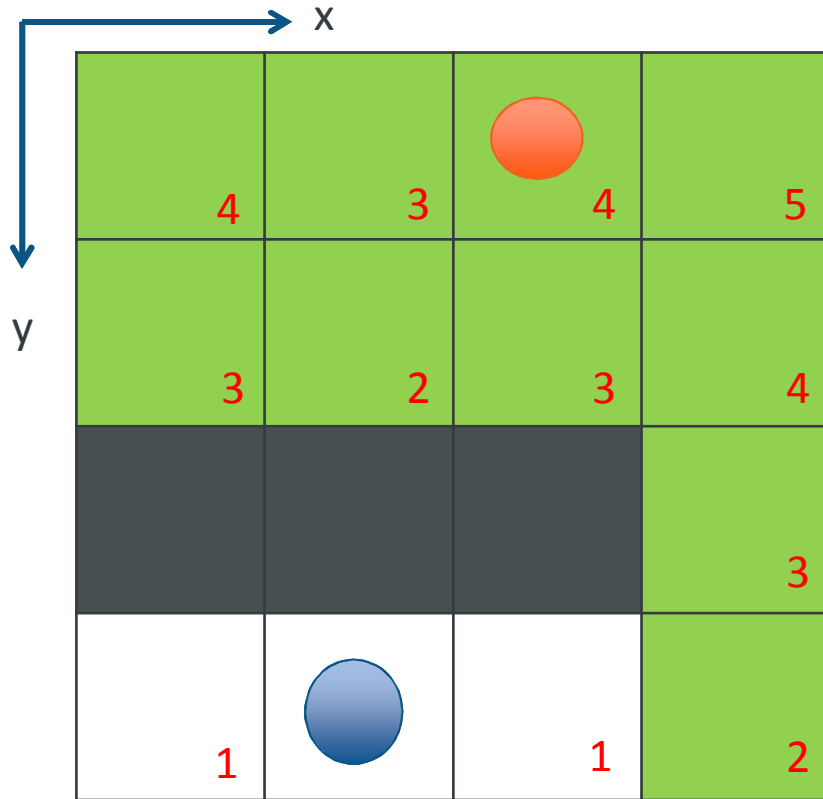
(2,4) $H(n) \text{ (Manhattan)} + g(n)=1$

Close list

(1,3)
(2,3)
(3,3)
(3,1)
(2,1)
(3,2)
(2,2)
(1,2)
(1,1)
(4,2)



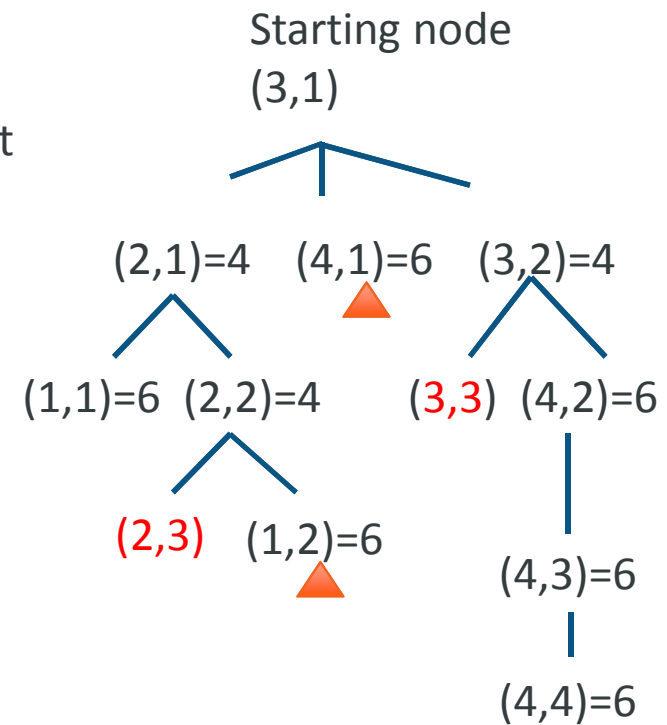
A*- Path Planning



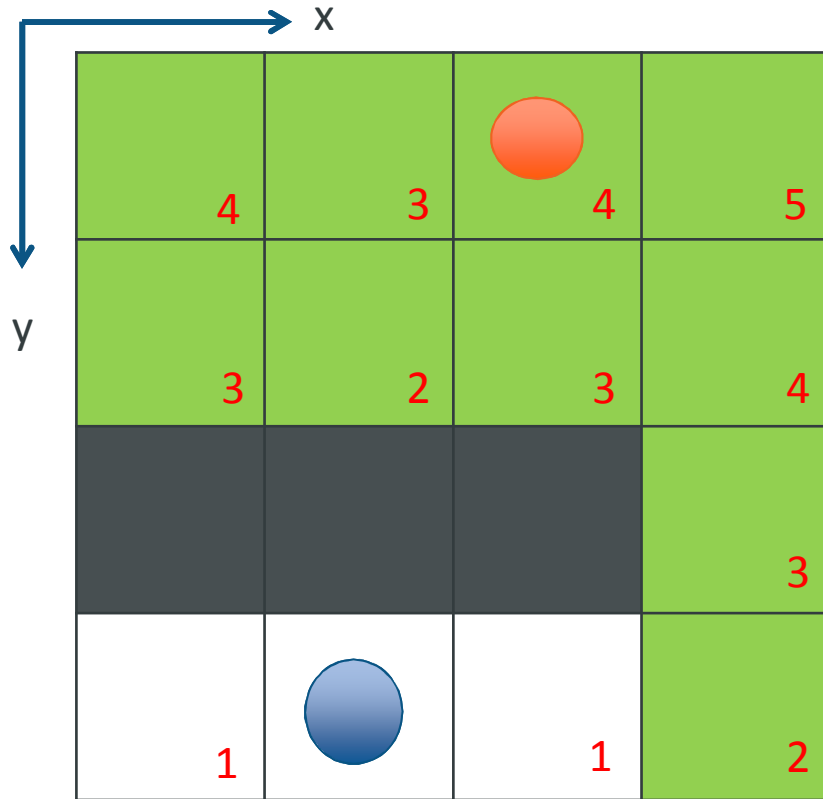
(2,4) $H(n) \text{ (Manhattan)} + g(n)=1$

Close list

(1,3)
(2,3)
(3,3)
(3,1)
(2,1)
(3,2)
(2,2)
(1,2)
(1,1)
(4,2)
(4,3)



A*- Path Planning



(2,4)

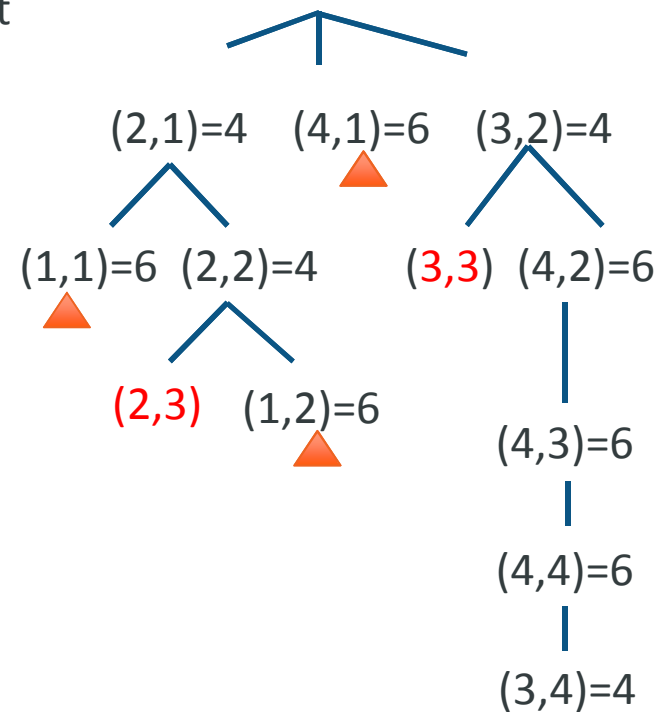
$H(n)$ (Manhattan) + $g(n)=1$

Close list

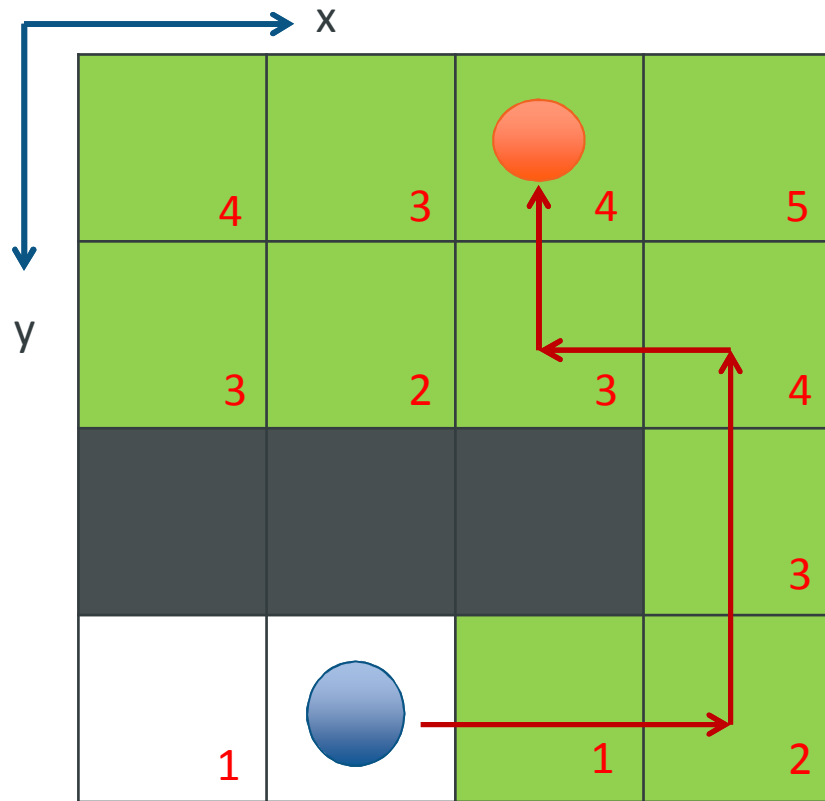
(1,3)
(2,3)
(3,3)
(3,1)
(2,1)
(3,2)
(2,2)
(1,2)
(1,1)
(4,2)
(4,3)
(4,4)

Starting node

(3,1)



A*- Path Planning



(2,4)

$H(n)$ (Manhattan) + $g(n)=1$

Close list

(1,3)

(2,3)

(3,3)

(3,1)

(2,1)

(3,2)

(2,2)

(1,2)

(1,1)

(4,2)

(4,3)

(4,4)

Current node

(3,4)=2

Open list

(2,4)=goal

Potential Fields

- Initially proposed for real-time collision avoidance [Khatib 1986].
- A potential field is a scalar function over the free space.
- To navigate, the robot applies a force proportional to the negated gradient of the potential field.
- A navigation function is an ideal potential field that
 - has global minimum at the goal
 - has no local minima
 - grows to infinity near obstacles
 - is smooth

Attractive & Repulsive Fields

$$F_{\text{att}} = -k_{\text{att}} (x - x_{\text{goal}})$$

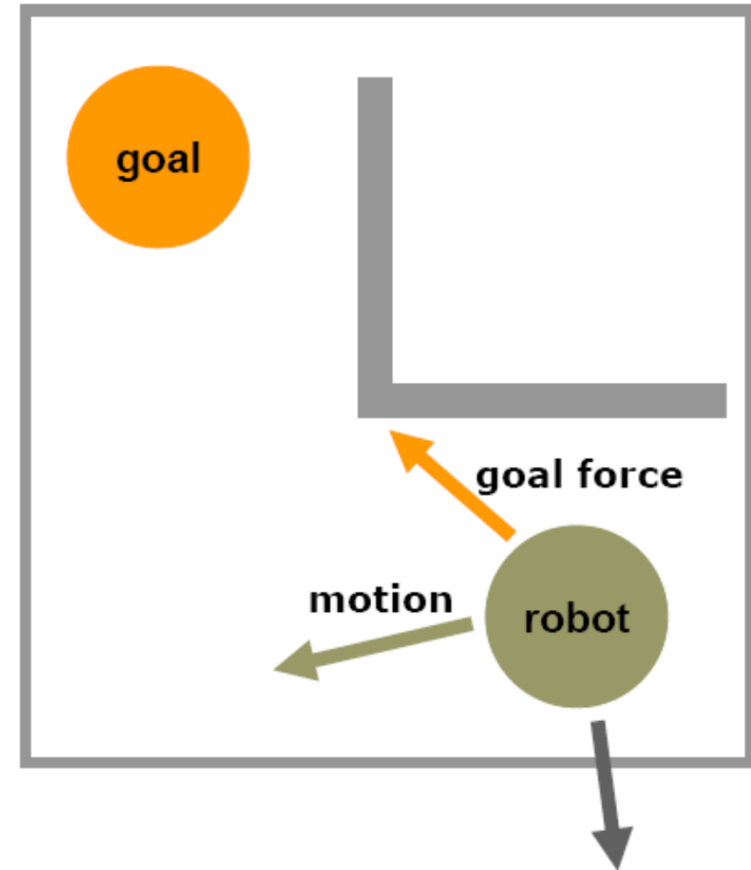
$$F_{\text{rep}} = \begin{cases} k_{\text{rep}} \left(\frac{1}{\rho} - \frac{1}{\rho_0} \right) \frac{1}{\rho^2} \frac{\partial \rho}{\partial x} & \text{if } \rho \leq \rho_0, \\ 0 & \text{if } \rho > \rho_0 \end{cases}$$

$k_{\text{att}}, k_{\text{rep}}$: positive scaling factors

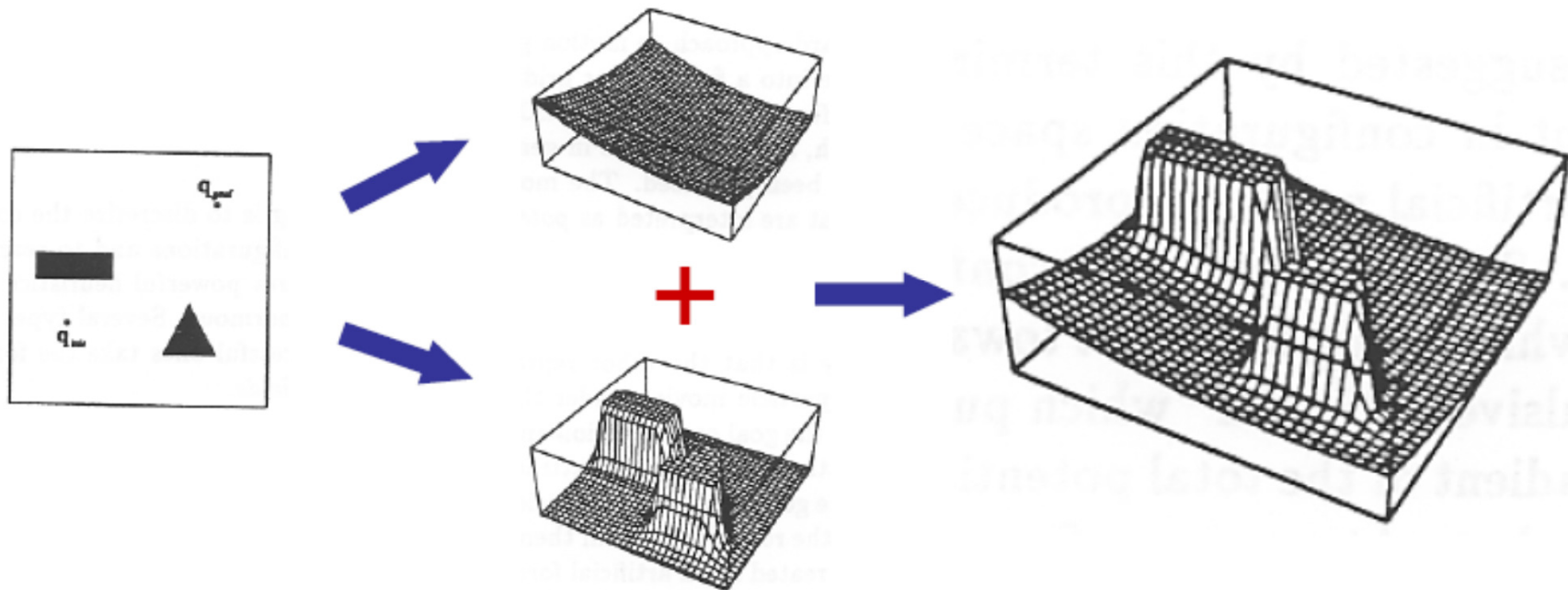
x : position of the robot

ρ : distance to the obstacle

ρ_0 : distance of influence



How Does It Work?



Algorithm Outline

- Place a regular grid G over the configuration space
- Compute the potential field over G
- Search G using a best-first algorithm-such as A^* with potential field as the heuristic function

Local Minima

- What can we do?
 - Escape from local minima by taking random walks
 - Build an ideal potential field – navigation function – that does not have local minima

