

# Lecture 10

## Planning - II - Bugs

# Course Logistics

- **Quiz 8 was posted today and was due before the lecture.**
- Project 2 is posted on 10/02 and will be due 10/11.



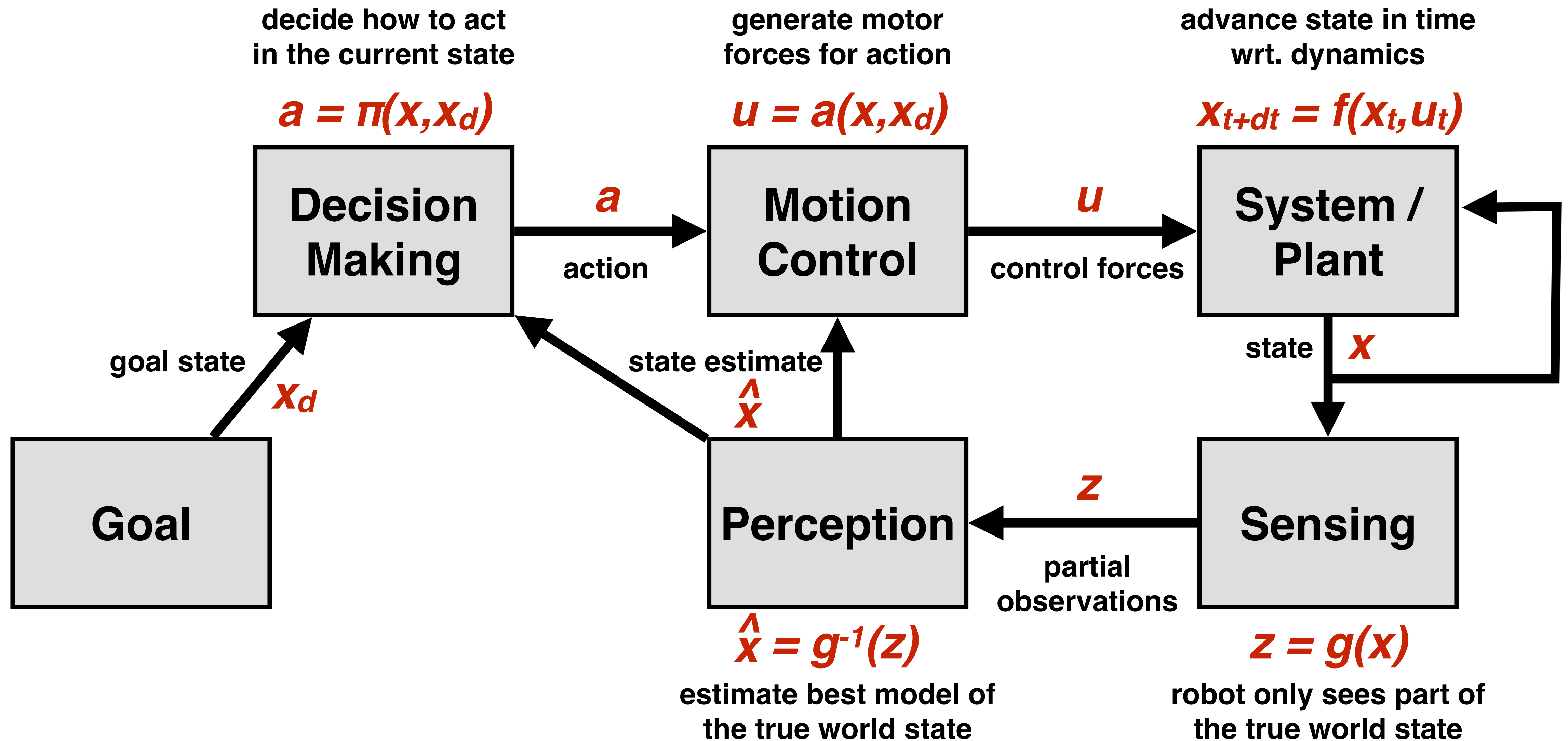
# Approaches to motion planning

- **Bug algorithms: Bug[0-2], Tangent Bug**
- Graph Search (fixed graph)
  - Depth-first, Breadth-first, Dijkstra, A-star
- Sampling-based Search (build graph):
  - Probabilistic Road Maps, Rapidly-exploring Random Trees
- Optimization (local search):
  - Gradient descent, potential fields, Wavefront

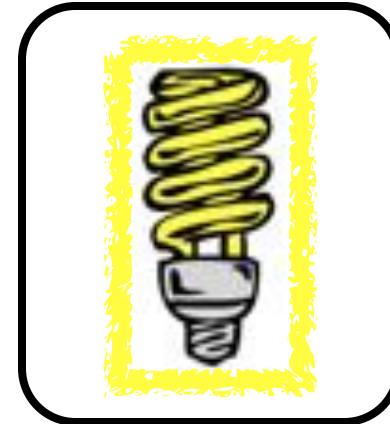




# Robot Control Loop

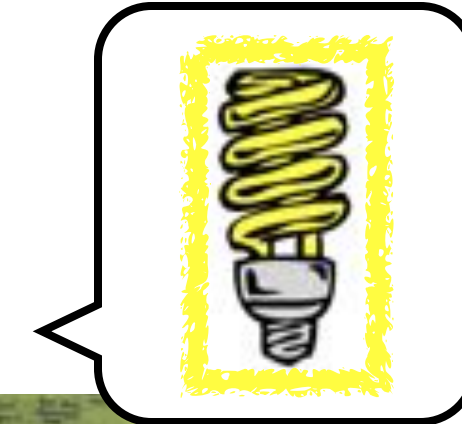


# Should your robot's decision making



fully think through  
solving a problem?

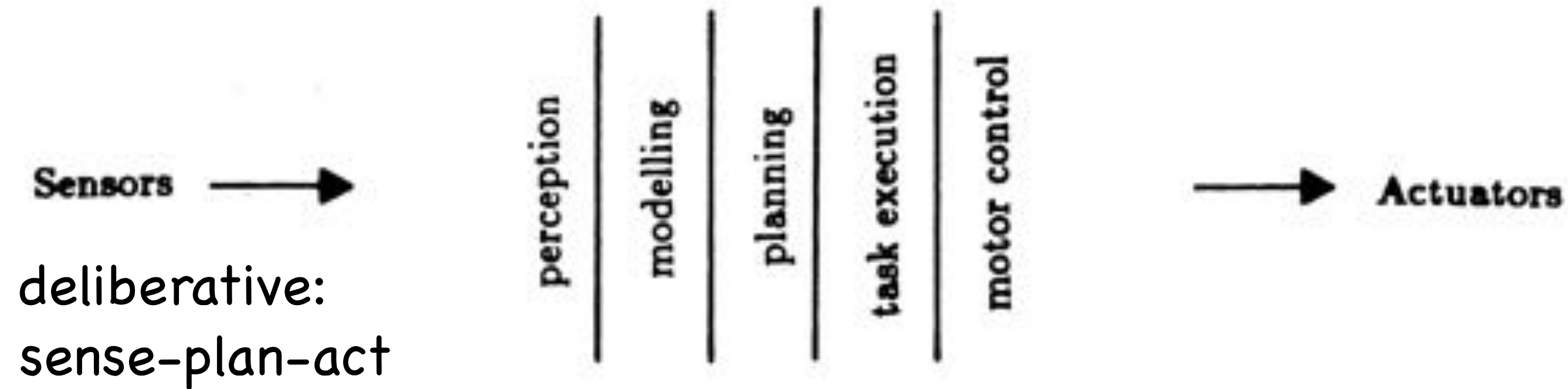
OR



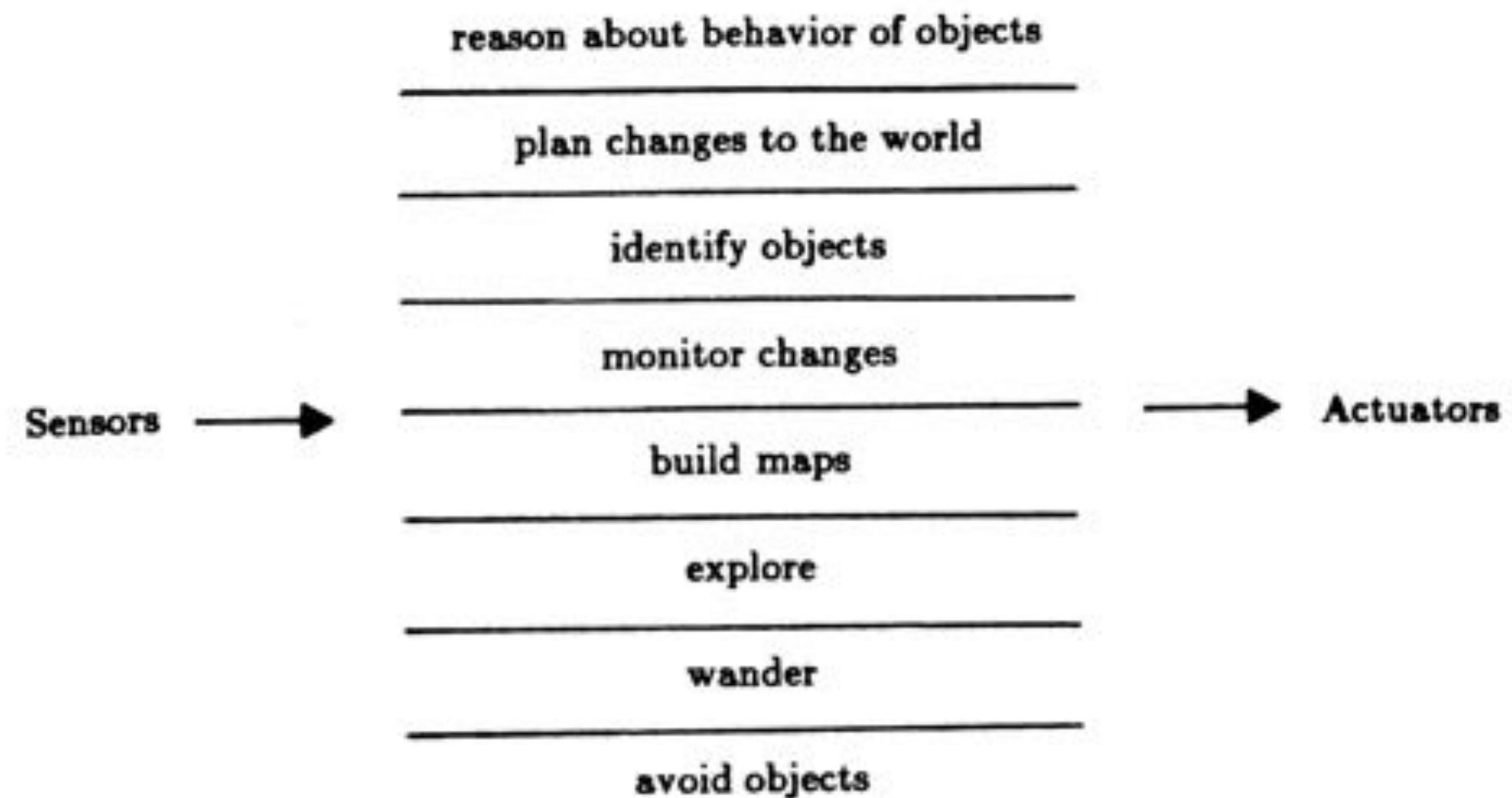
react quickly to  
changes in its world?



# Deliberation v. Reaction



reaction: subsumption,  
Finite State Machine  
controllers act in parallel

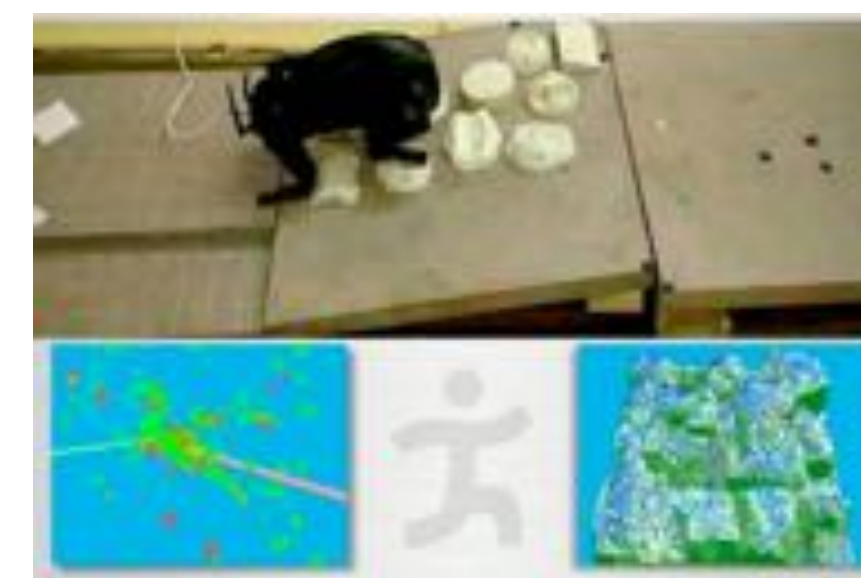
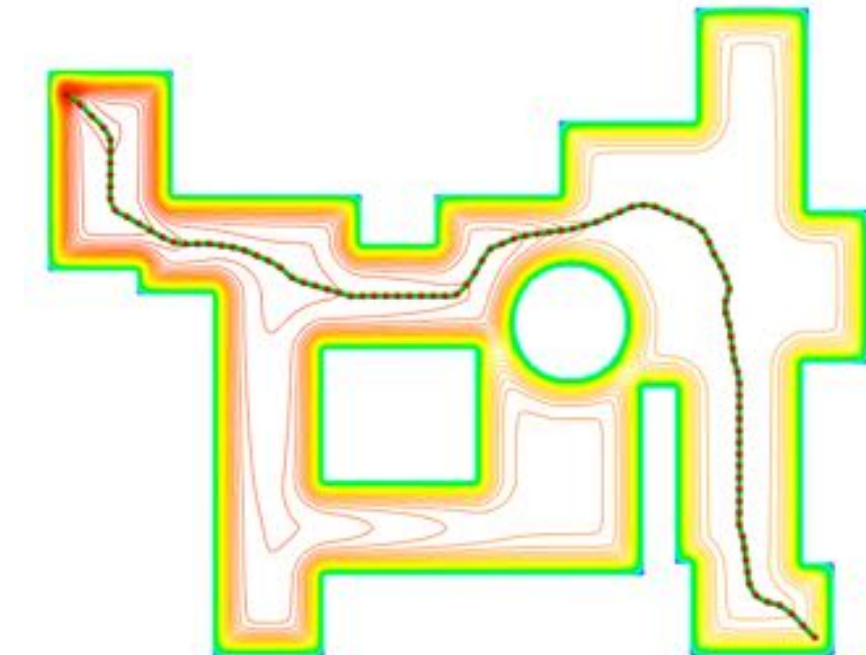
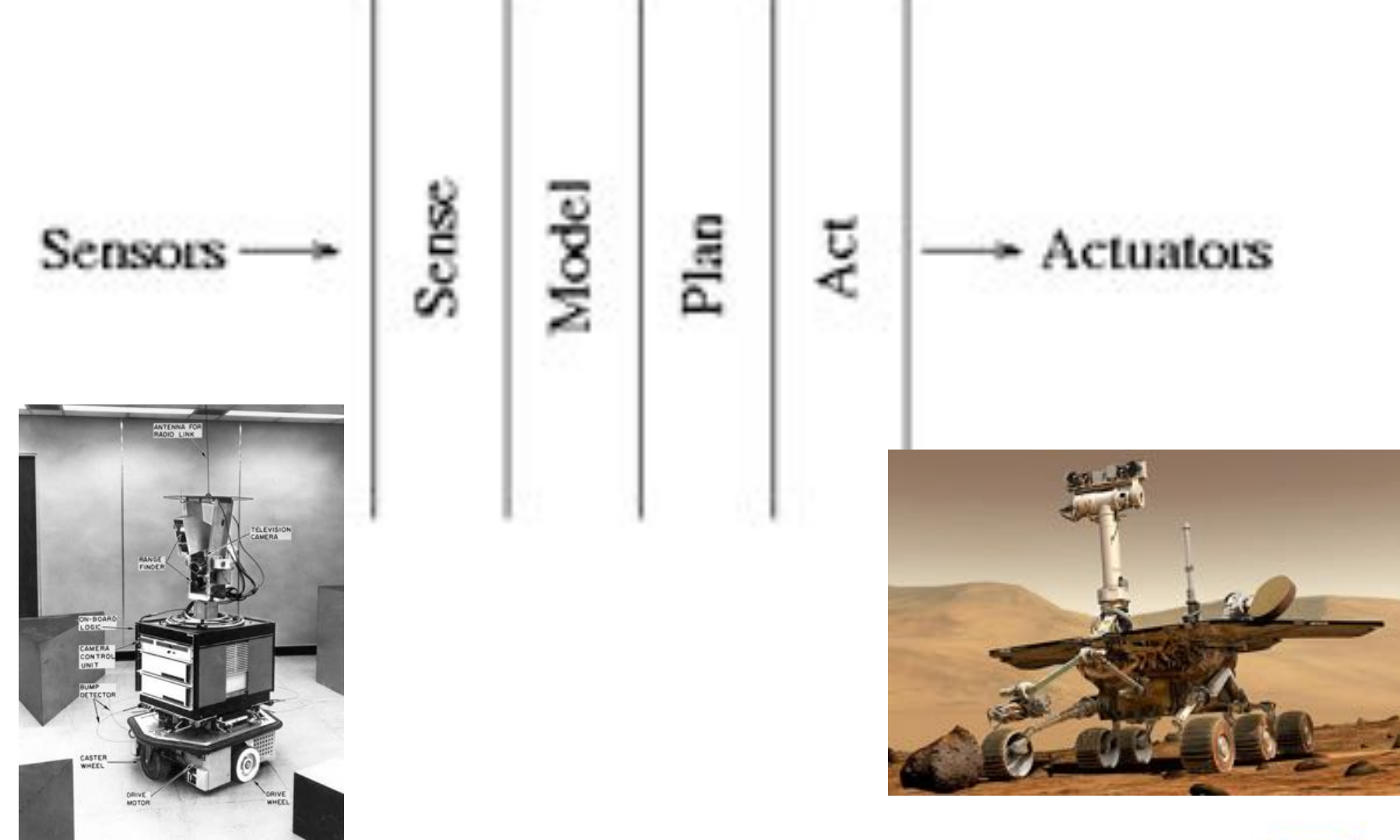




# Deliberation

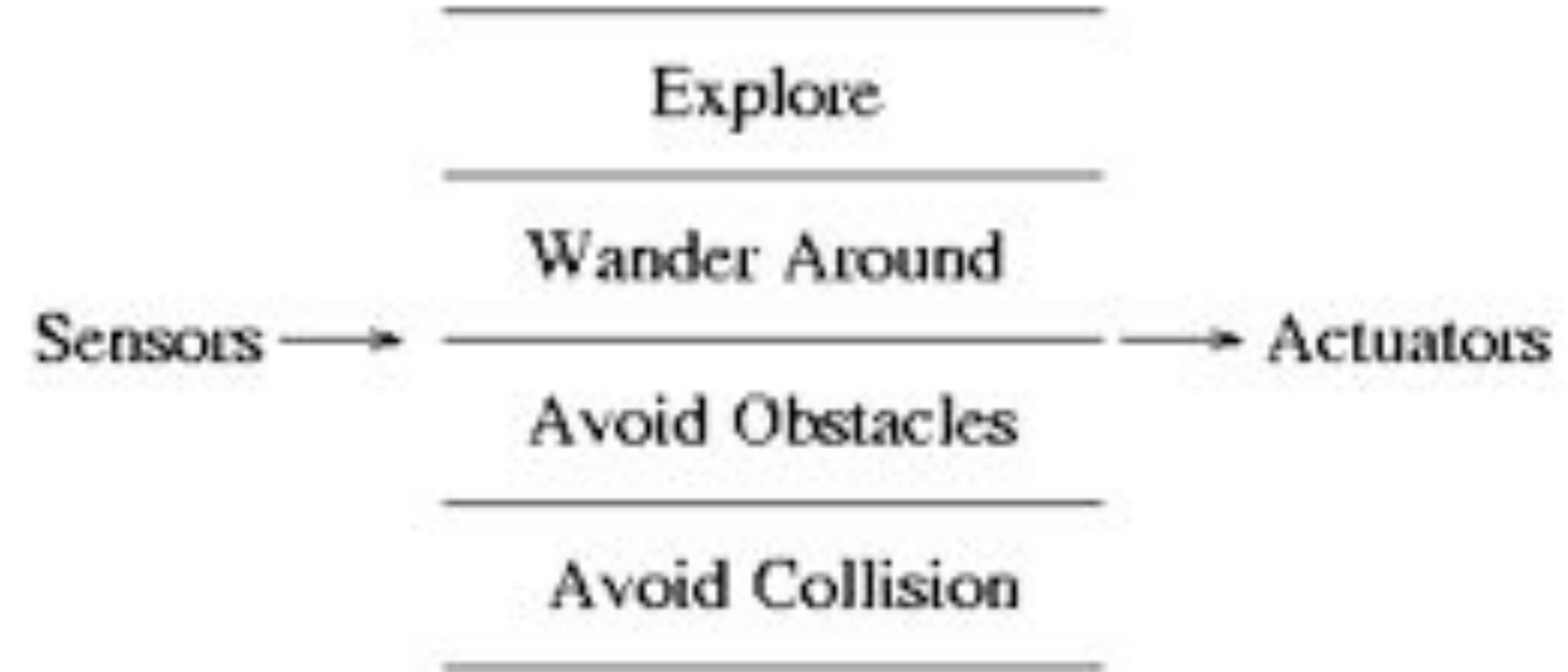
## “Sense-Plan-Act” paradigm

- sense: build most complete model of world
  - GPS, SLAM, 3D reconstruction, affordances
- plan: search over all possible outcomes
  - BFS, DFS, Dijkstra, A\*, RRT
- act: execute plan through motor forces





# Reaction



- No representation of state
- Typically, fast hardcoded rules
- Embodied intelligence
  - behavior := control + embodiment
  - ant analogy, stigmergy
- Subsumption architecture
  - prioritized reactive policies
- Ghengis hexpod video







MIT Genghis

<https://www.youtube.com/watch?v=1j6CliOwRng>





Robots have to make lots of decisions



# Base Navigation

- How get from point A to point B
- **What is the simplest policy to perform navigation?**
  - Remember: simplest reactive policy?



# Random Walk: Goal Seeking

- Move in a random direction until you hit something
- Then go in a new direction
- Stop when you get to the goal, assuming it can be recognized



Lisa Miller, <http://www.youtube.com/watch?v=VBzXDrz8rMI>

goal: exit here





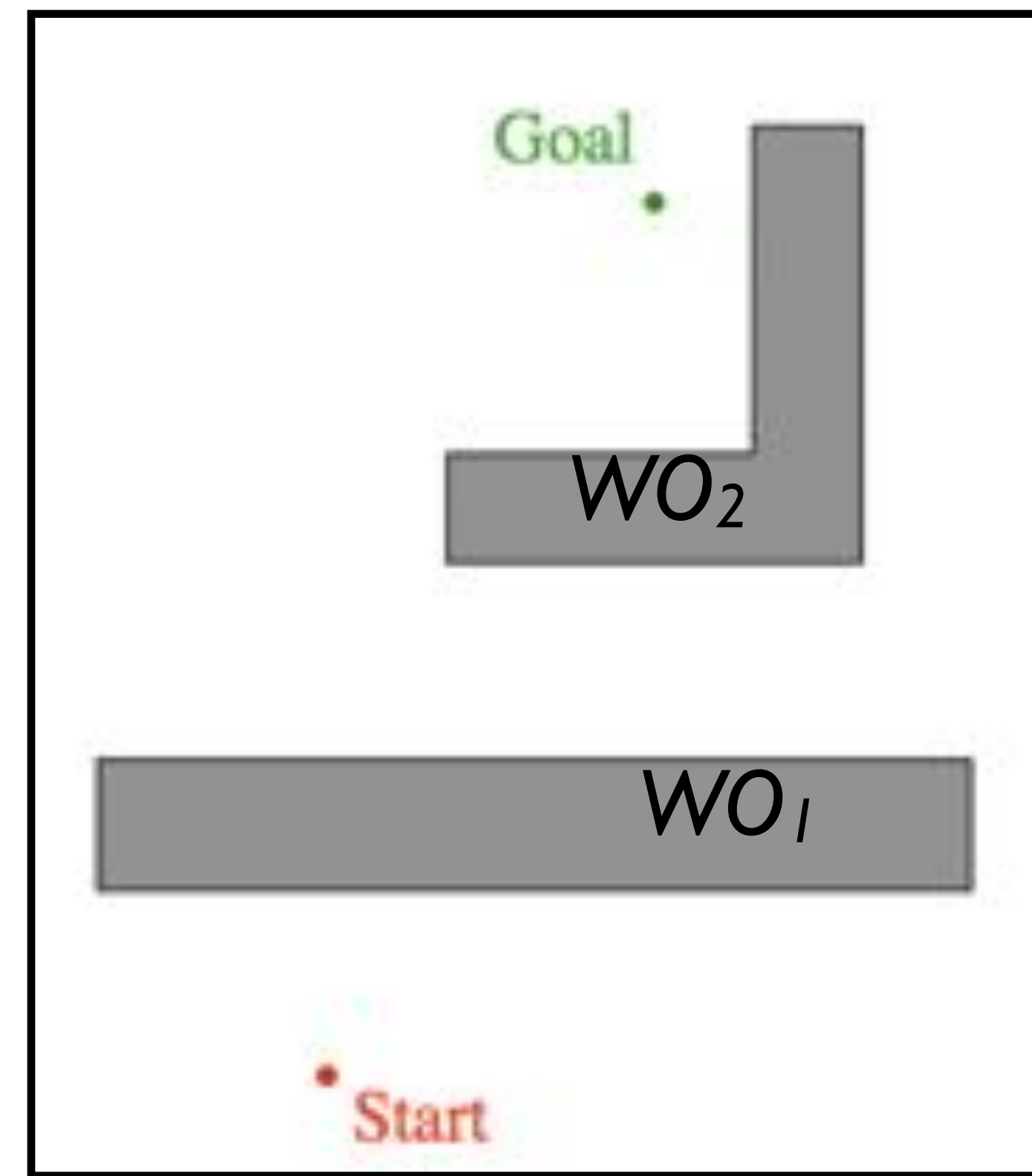
# Base Navigation

- How get from point A to point B
- What is the simplest policy to perform navigation?
  - random walk
  - reactive: embodied intelligence
- **What is a “simple” deliberative policy?**



# Bug Algorithms

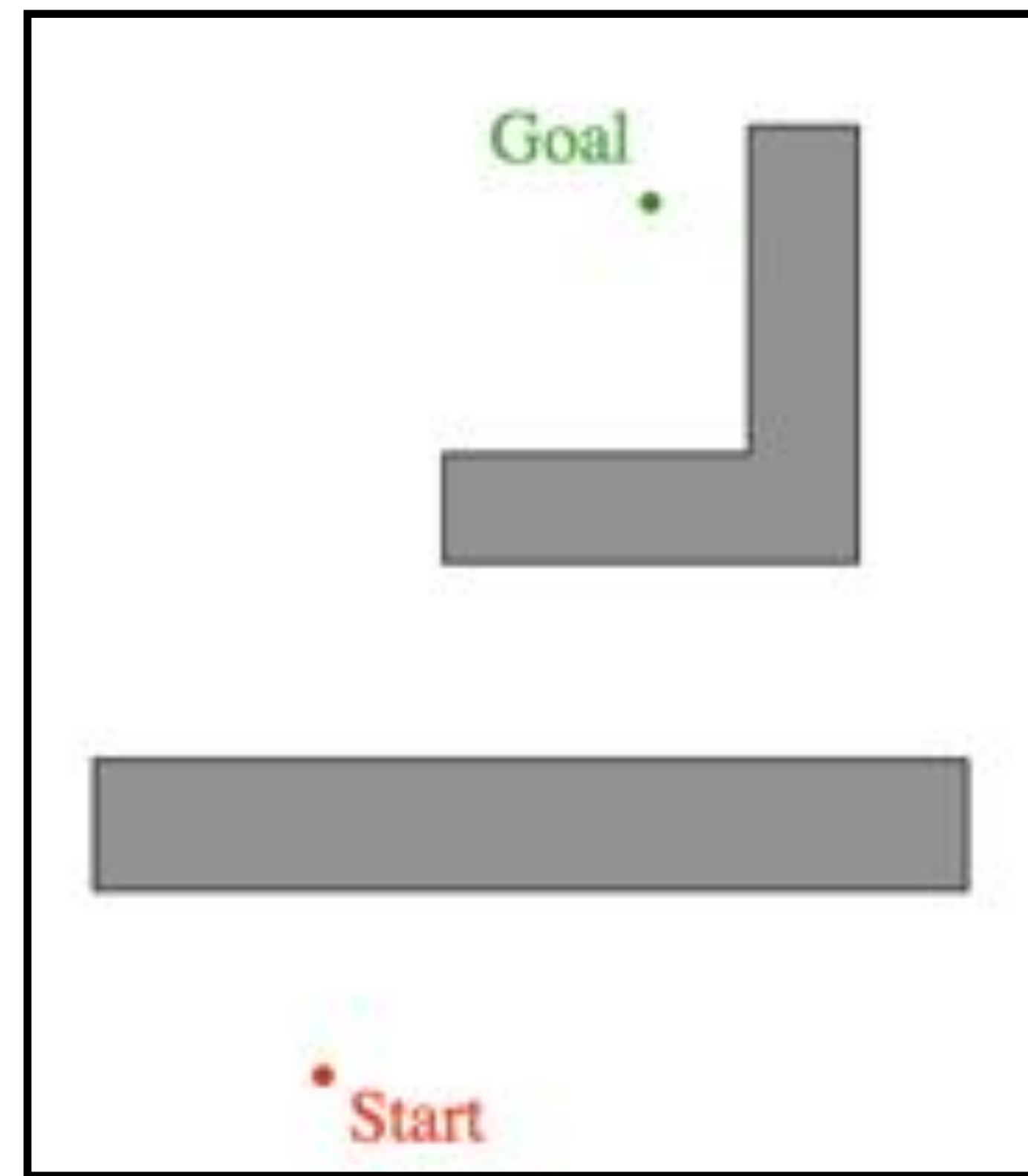
- Assume bounded world  $W$
- Known: global goal
  - measurable distance  $d(x,y)$
- Unknown: obstacles  $WO_i$
- Local sensing
  - tactile
  - distance traveled





# Bug Algorithms

- Assume bounded world  $W$
- Known: global goal
  - measurable distance  $d(x,y)$
- Unknown: obstacles  $WO_i$
- Local sensing
  - **bump sensor**
  - distance traveled



≈

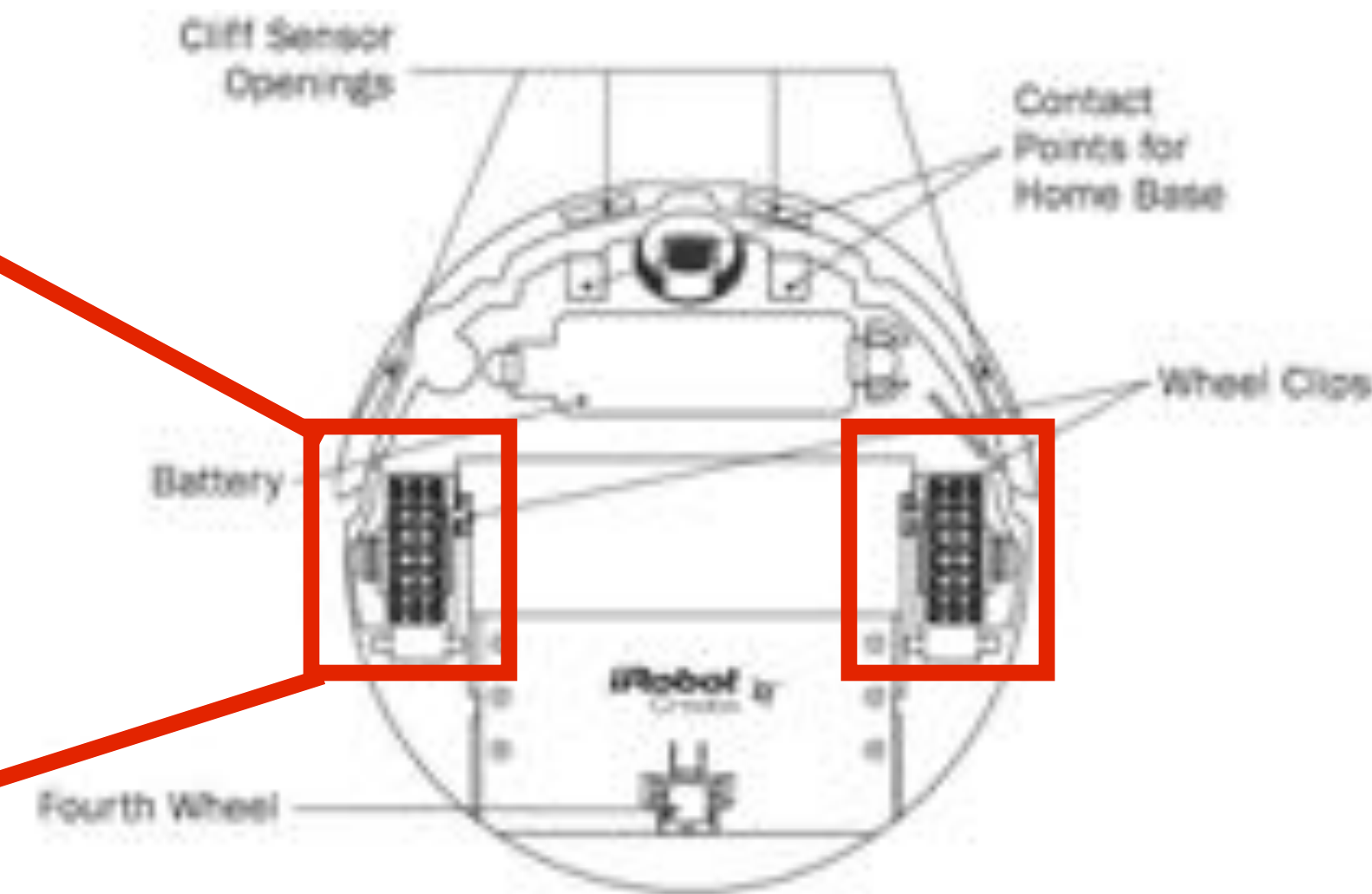
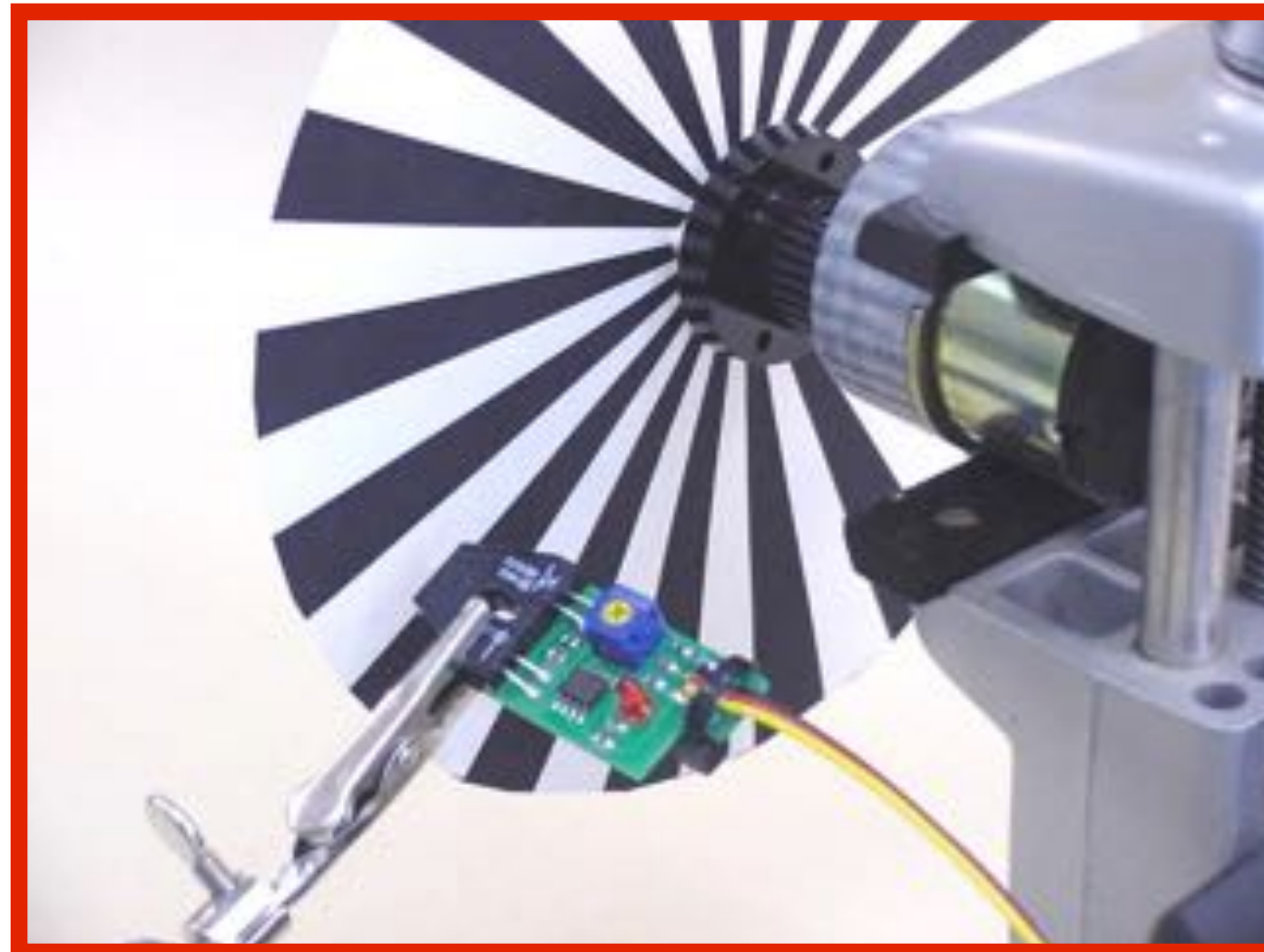


bumper is essentially an on/off button

# Bug

## Optical encoders

- Assume
- Known:
- measure
- Unknown
- Local sensing
- bump
- odometry



≈





# Interesting application of Bug algorithms ?





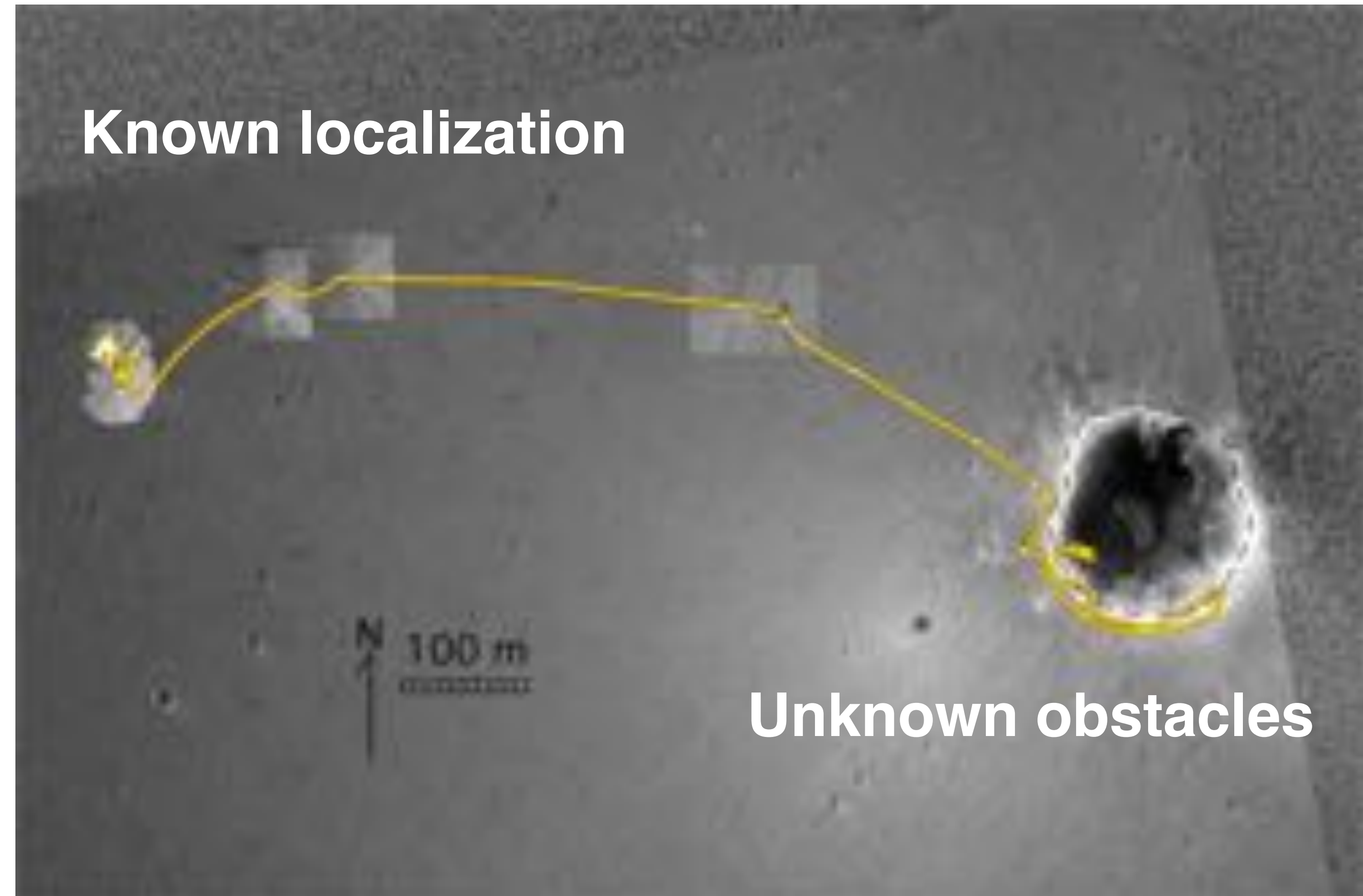


# Mars Exploration Rover

<http://mars.nasa.gov/mer/gallery/press/opportunity/20040921a.html>



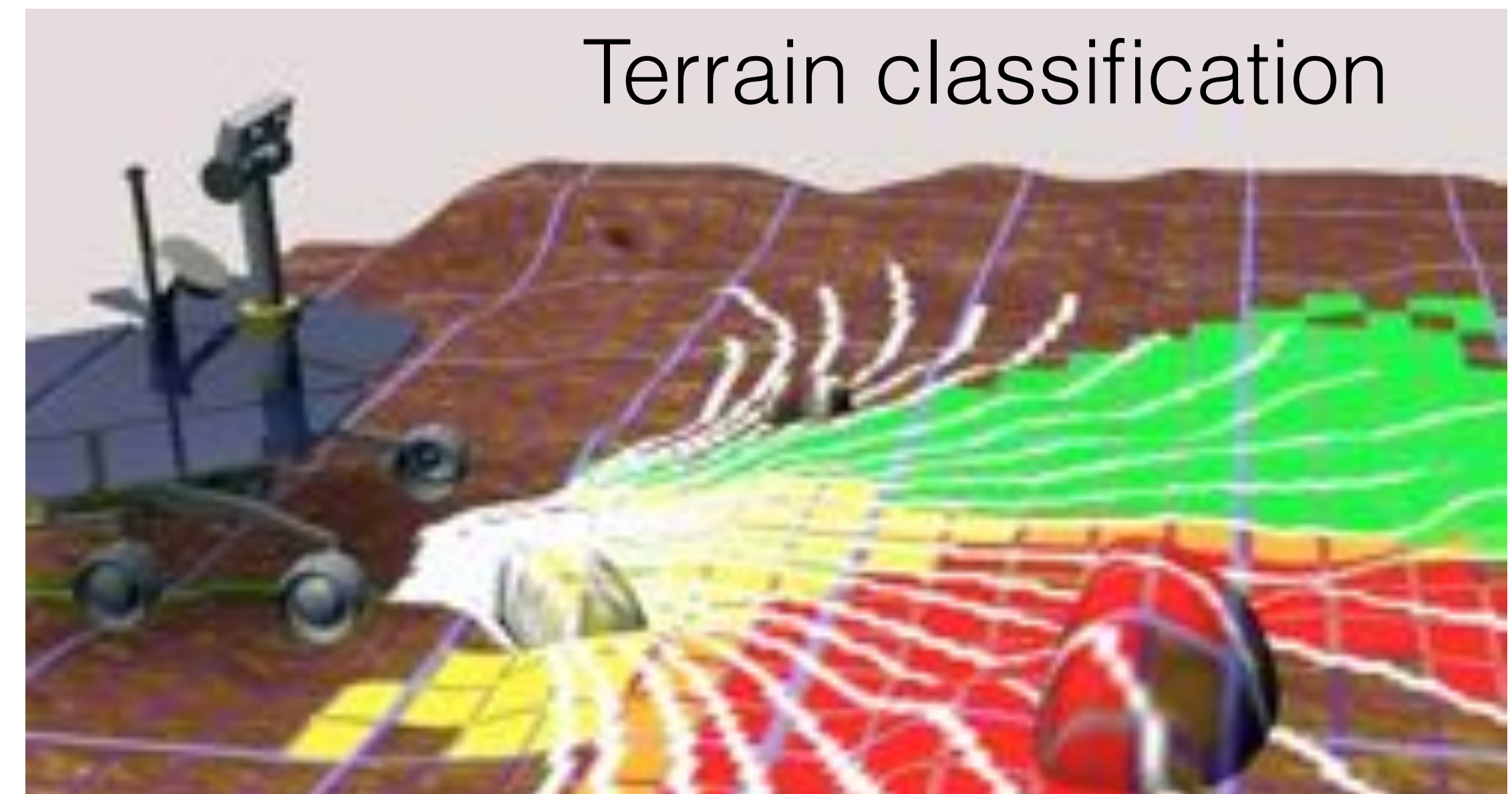
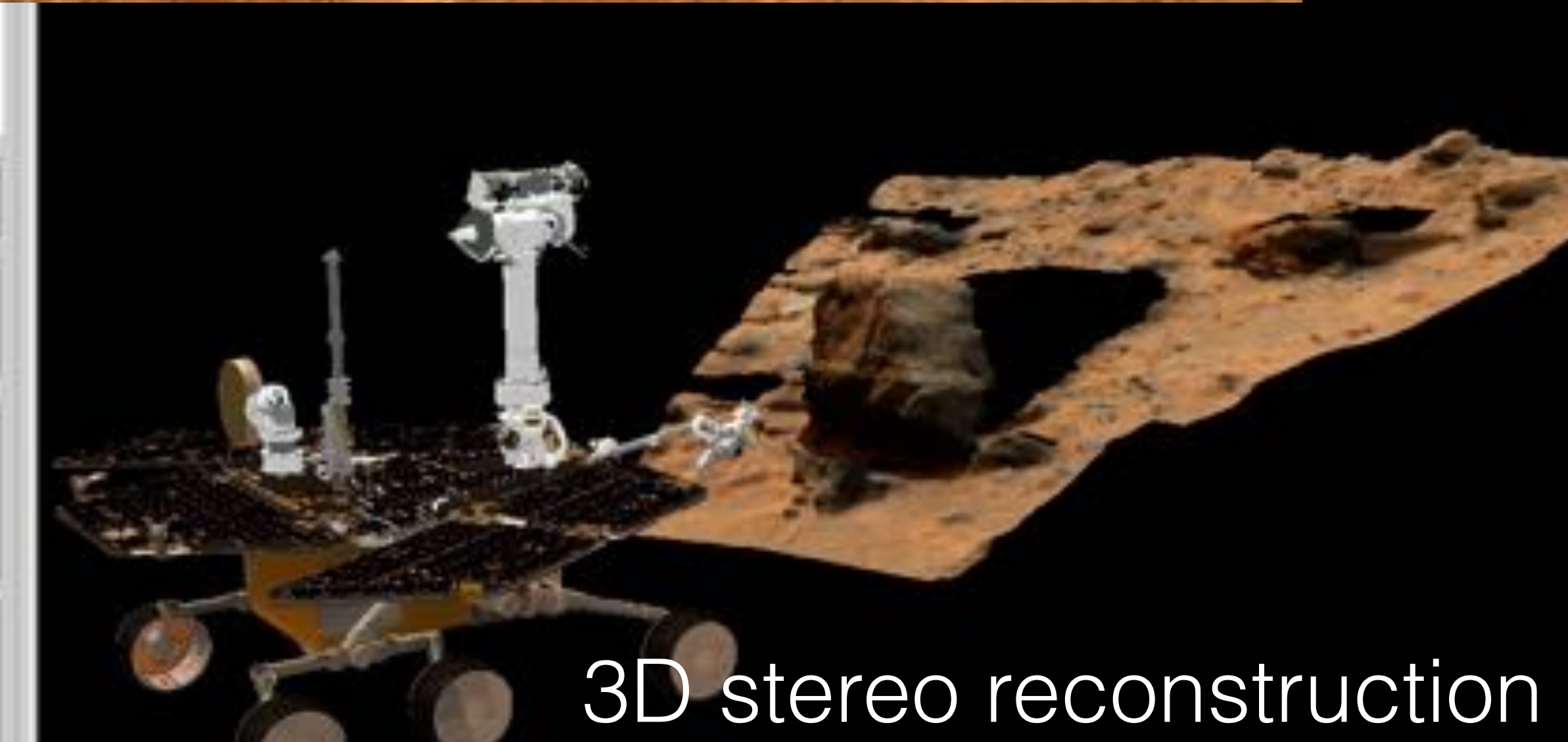
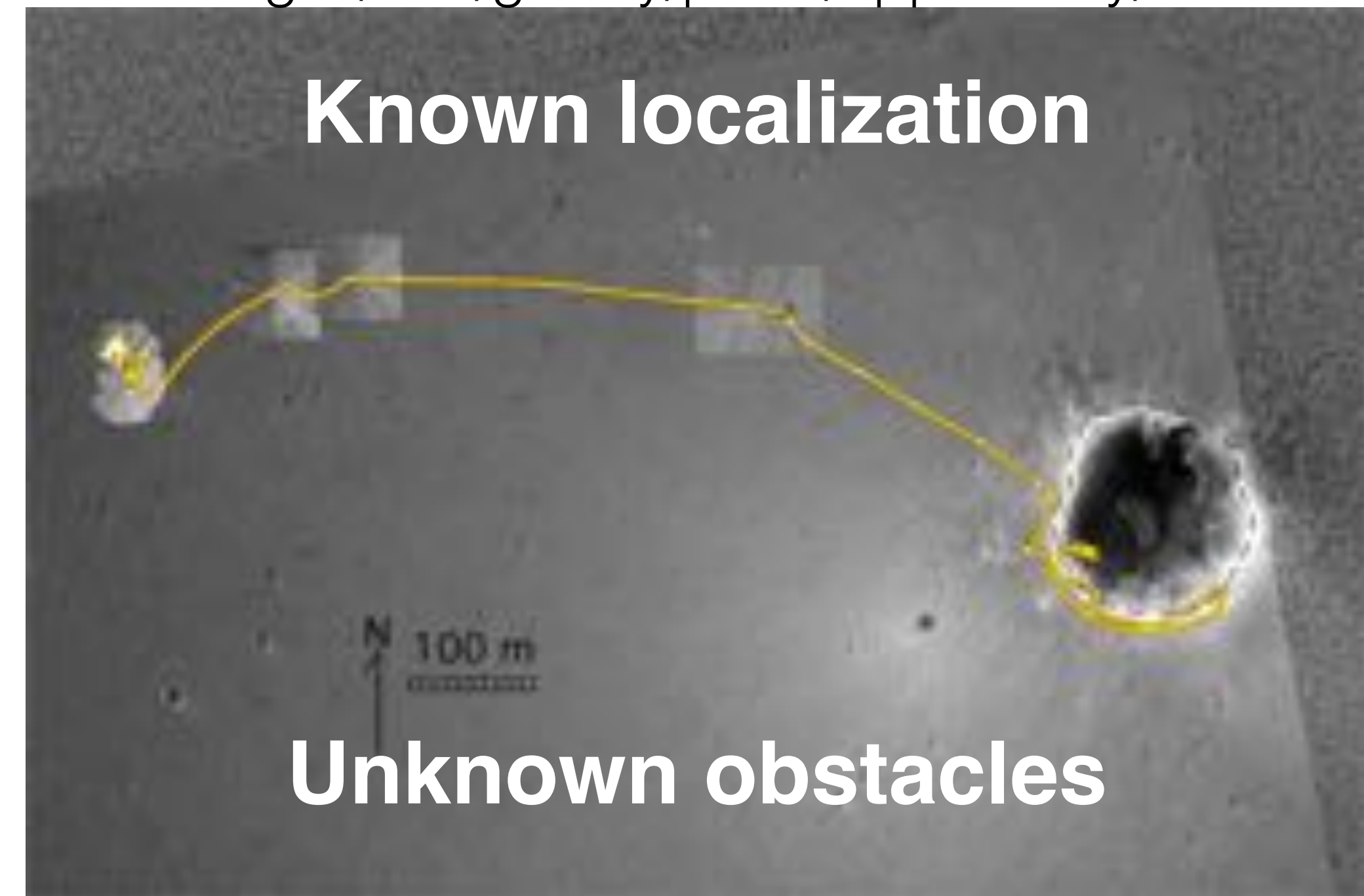
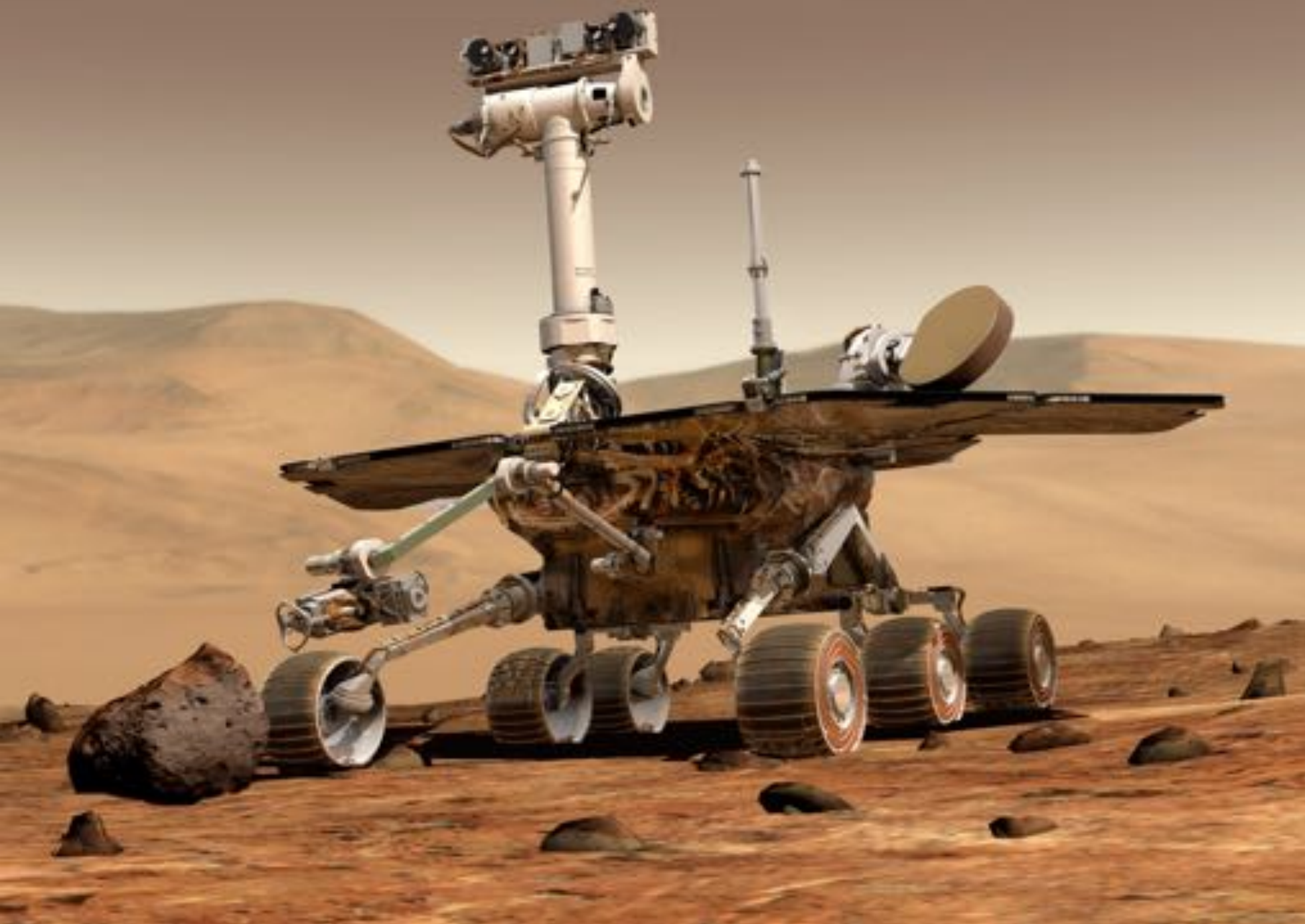
**Known localization**





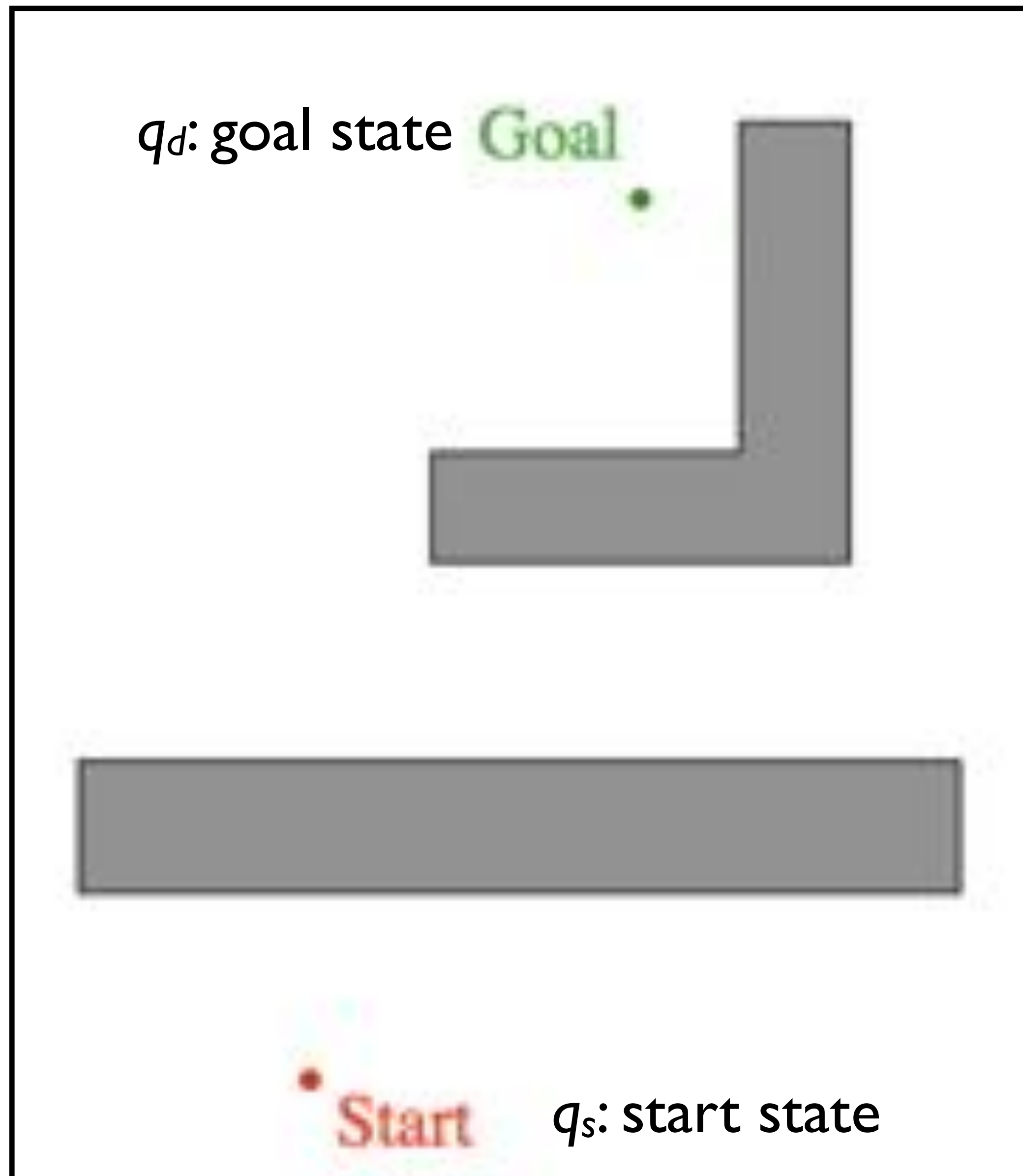
# Mars Exploration Rover

<http://mars.nasa.gov/mer/gallery/press/opportunity/20040921a.html>





# Bug Navigation

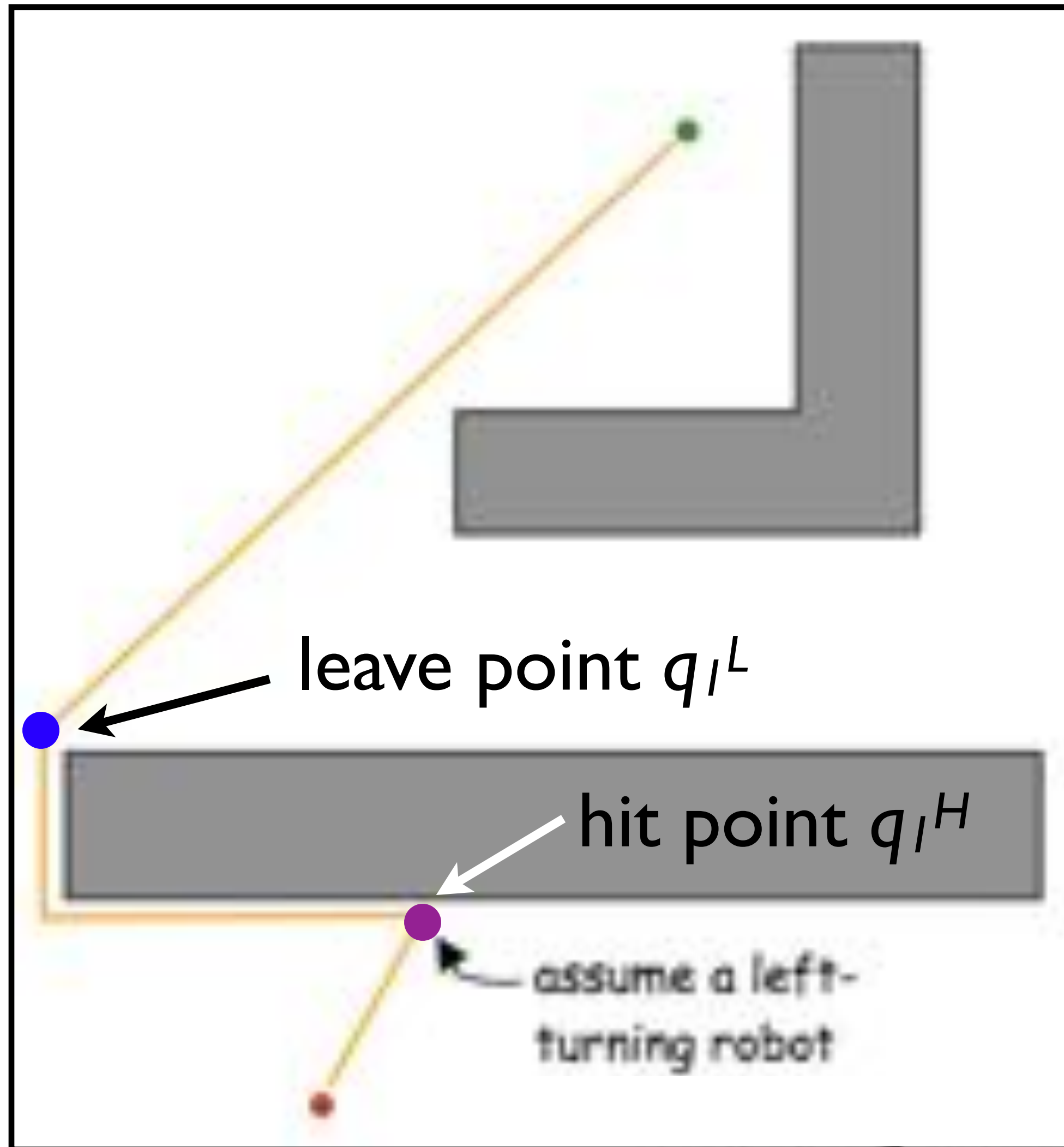


Plan navigation path from start  $q_s$   
to goal  $q_d$

as a sequence of hit/leave point  
pairs on obstacles

Hit point:  $q_i^H$   
Leave point:  $q_i^L$

# Bug 0



1) Head towards goal

2) When hit point set, **follow wall**, until you can move towards goal again (leave point)

3) continue from (1)



# Wall following

follow wall



One approach:

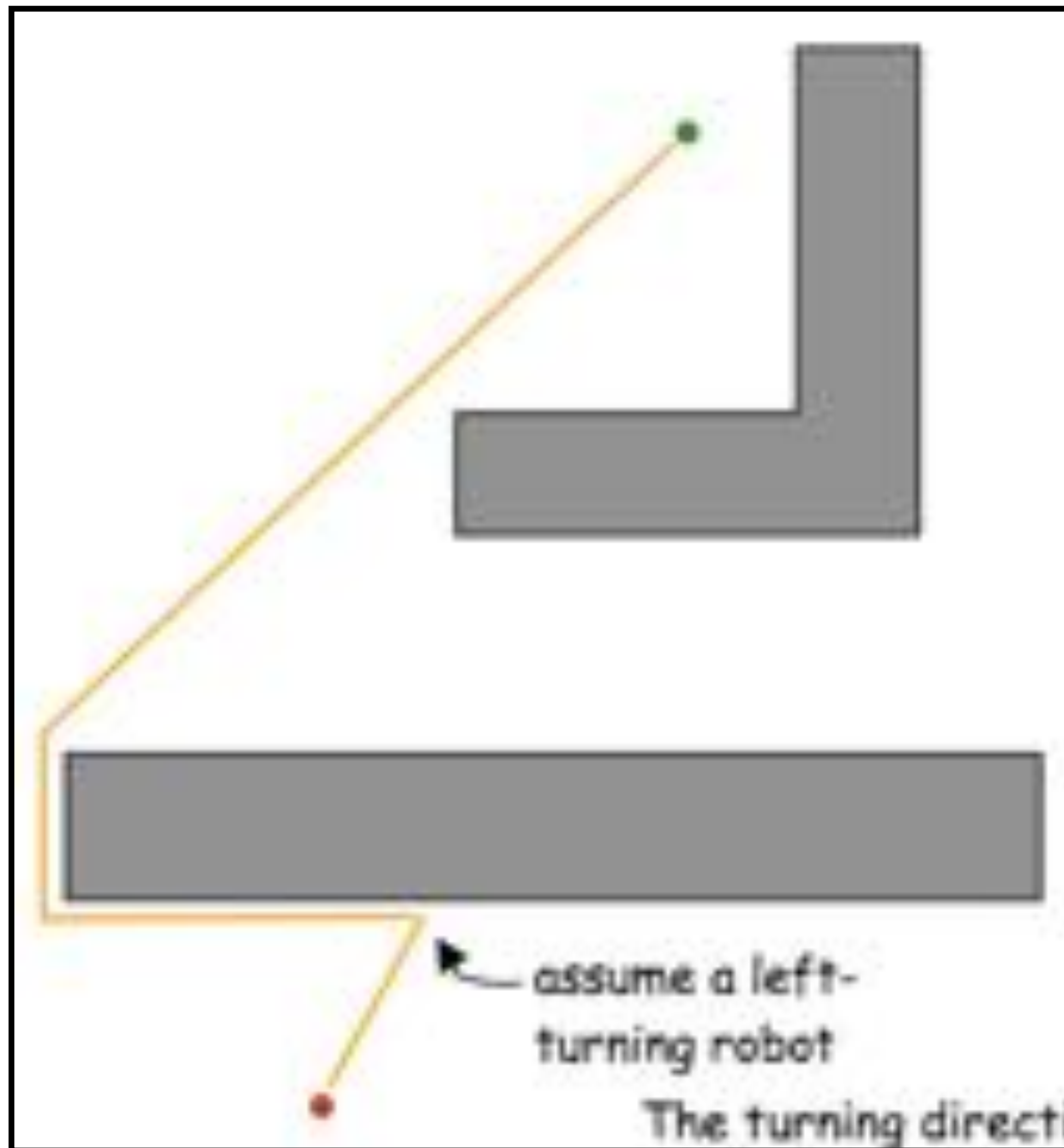
- a)* move forward with slight turn
- b)* when bumped, turn opposite direction
- c)* goto (*a*)

Trevor Jay



What map would foil Bug 0?

# Bug 0



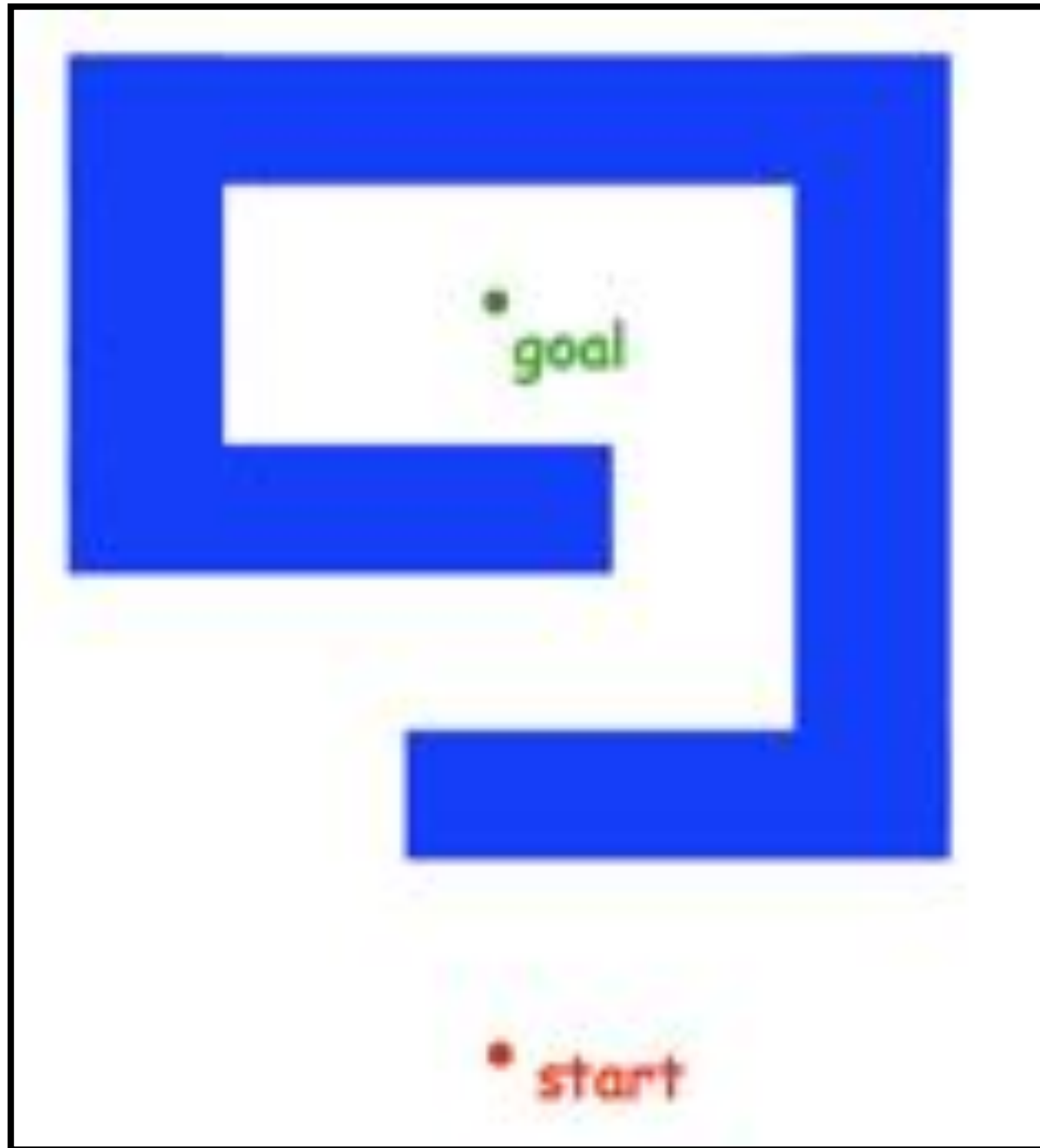
1) Head towards goal

2) When hit point set, follow wall, until you can move towards goal again (leave point)

3) continue from (1)



# Bug 0



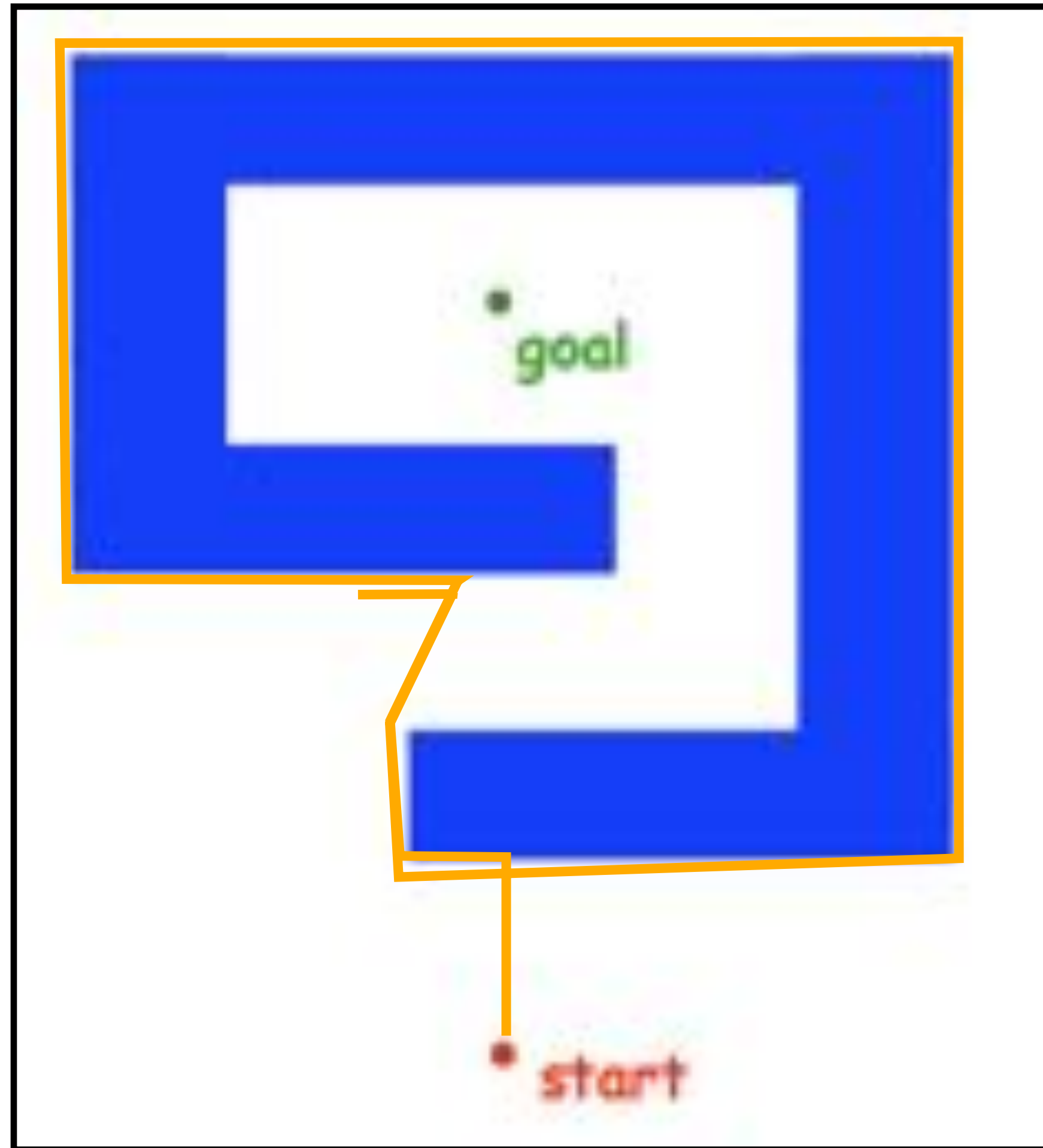
1) Head towards goal

2) When hit point set, follow wall, until you can move towards goal again (leave point)

3) continue from (1)

Can you trace the Bug 0 path?  
Can we make a better bug? How?

# Bug 0

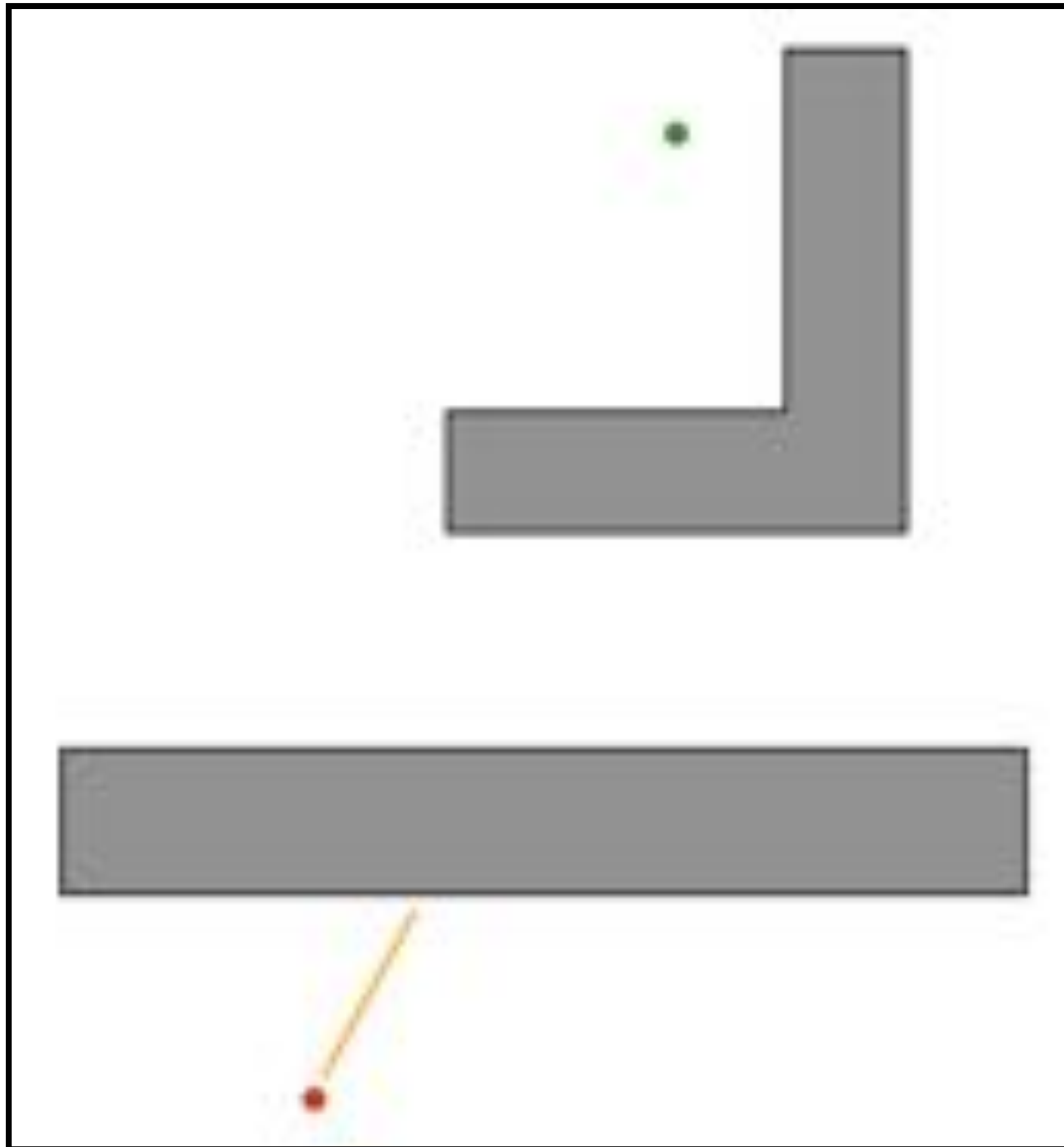


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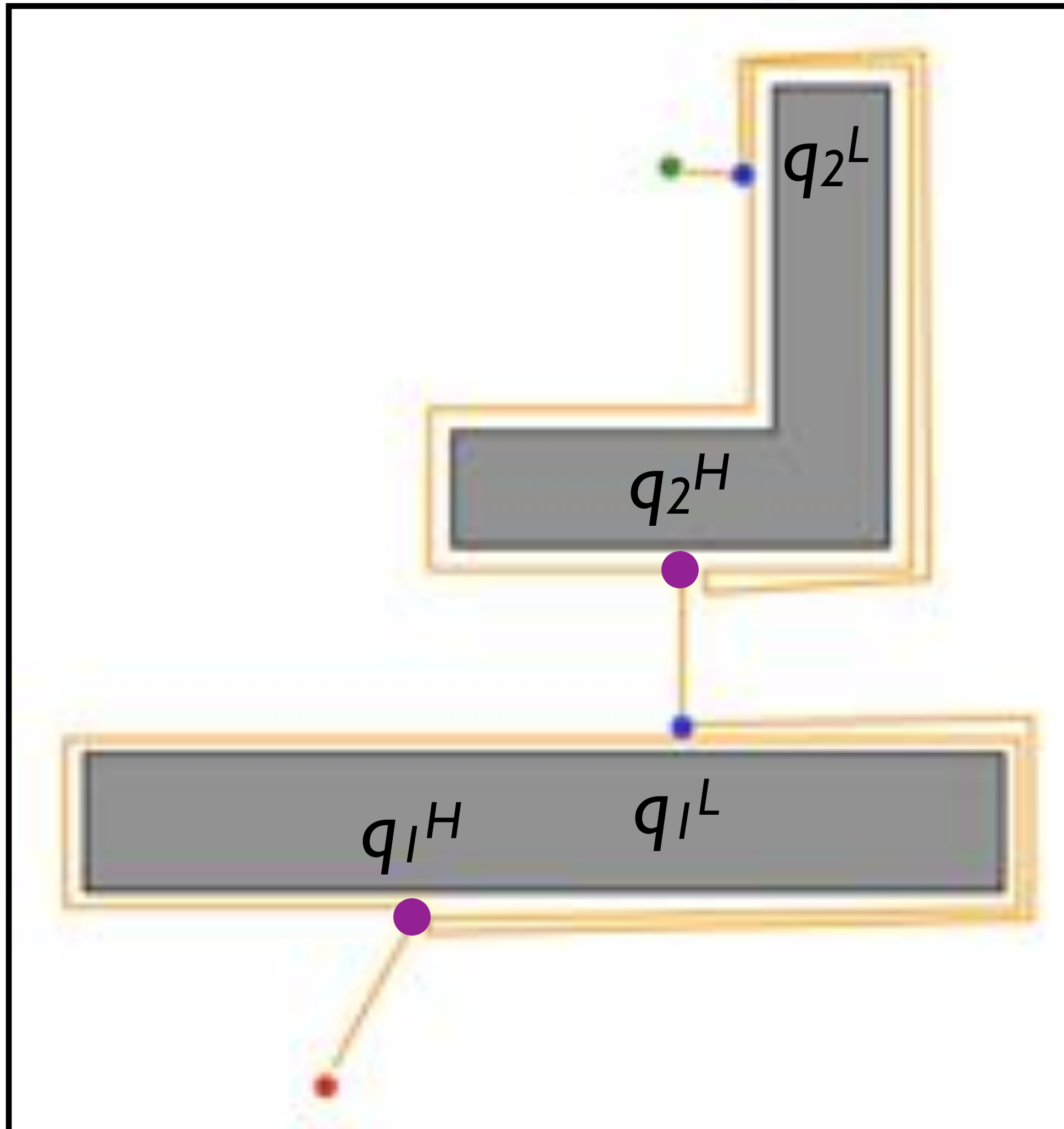


# Bug I



- 1) Head towards goal
- 2) When hit point set, circumnavigate obstacle, setting leave point as closest to goal
- 3) return to leave point
- 4) continue from (1)

# Bug I

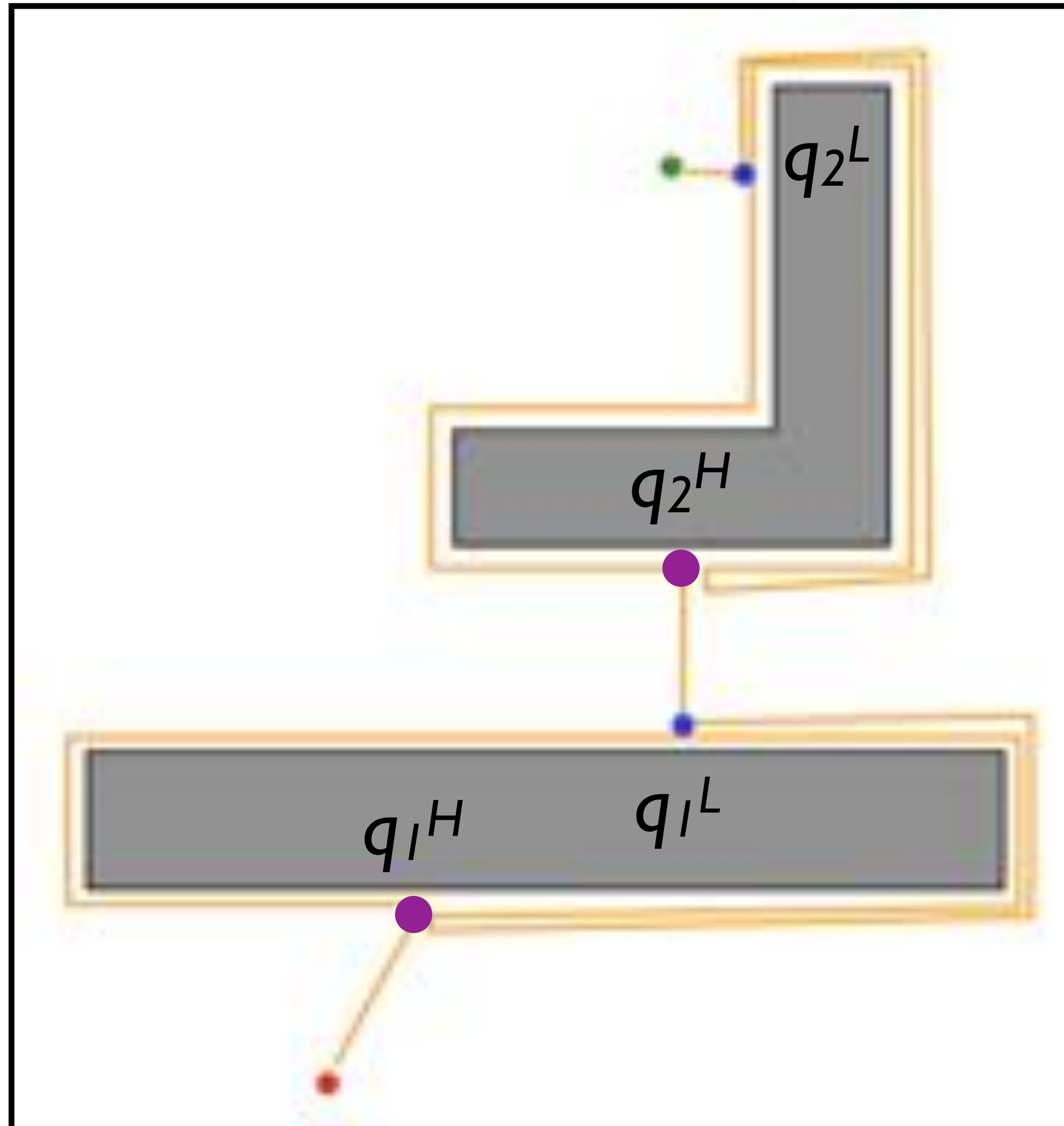


- 1) Head towards goal
- 2) When hit point set, circumnavigate obstacle, setting leave point as closest to goal
- 3) return to leave point
- 4) continue from (1)



What map would foil Bug 1?

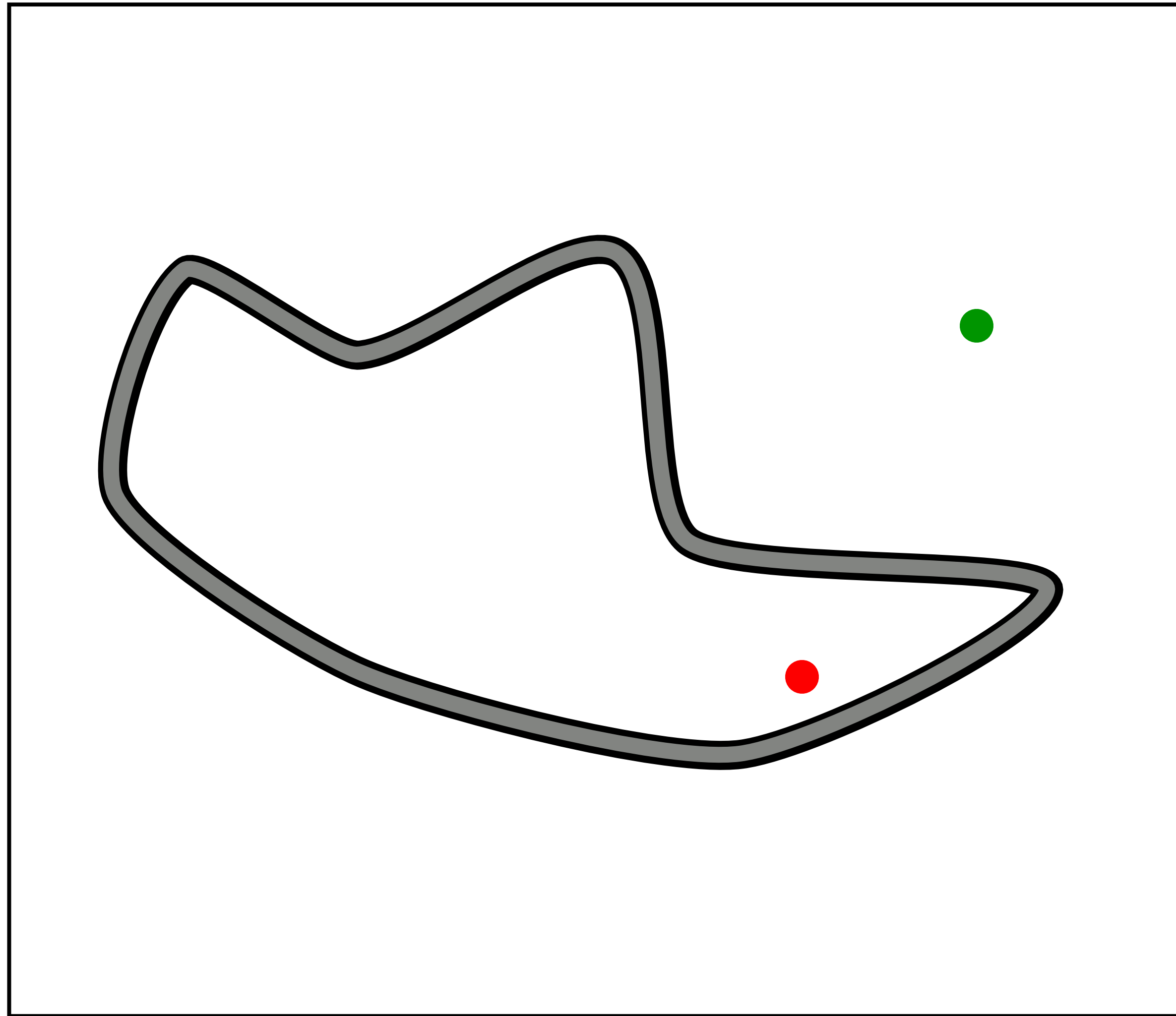
# Bug 1



- 1) Head towards goal
- 2) When hit point set, circumnavigate obstacle, setting leave point as closest to goal
- 3) return to leave point
- 4) continue from (1)

What map would foil Bug 1?

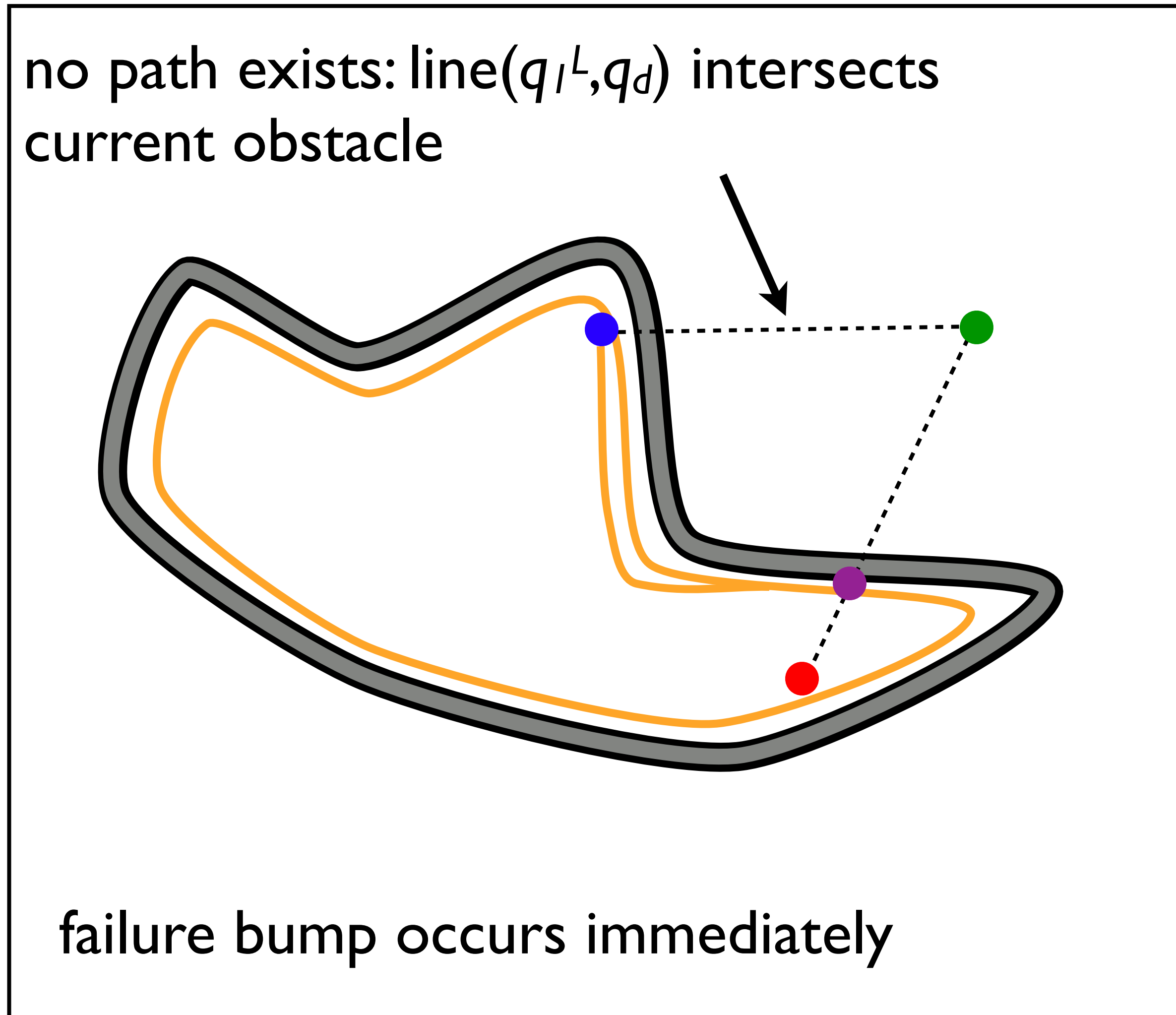
# Bug 1



- 1) Head towards goal
- 2) When hit point set, circumnavigate obstacle, setting leave point as closest to goal
- 3) return to leave point
- 4) if bump current obstacle, return fail; else, continue from (1)



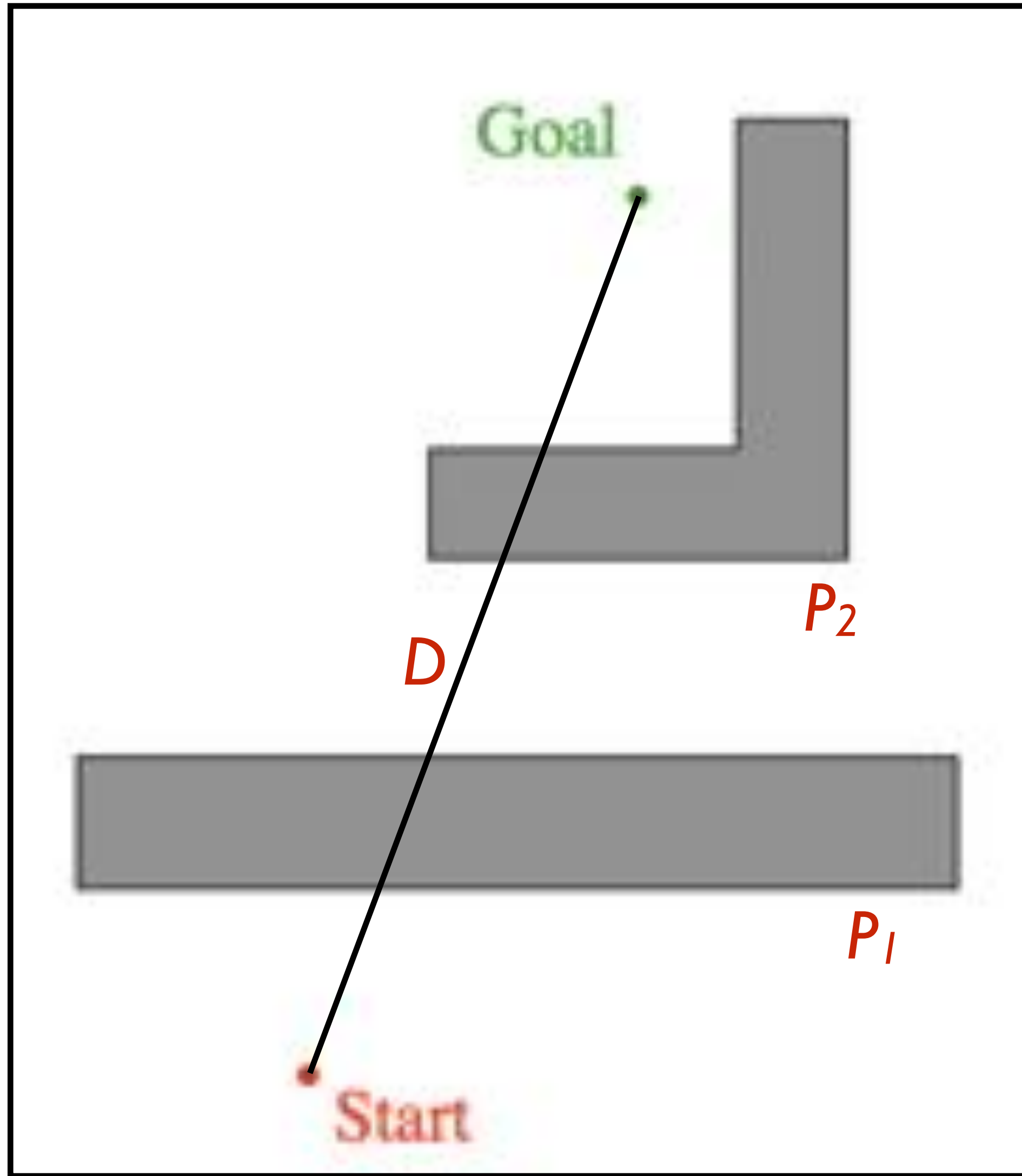
What map would foil Bug 1?



# Bug 1: Detecting Failure

- 1) Head towards goal
- 2) When hit point set, circumnavigate obstacle, setting leave point as closest to goal
- 3) return to leave point
- 4) if bump current obstacle, return **fail**;  
else, continue from (1)

# Bug 1: Search Bounds

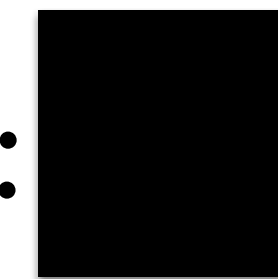


Bounds on path distance, assuming

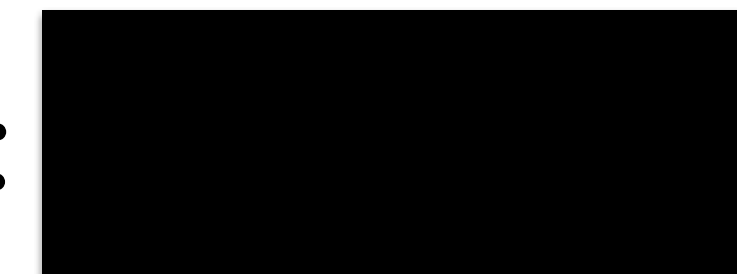
$D$ : distance start-to-goal

$P_i$ : obstacle perimeter

Best case:

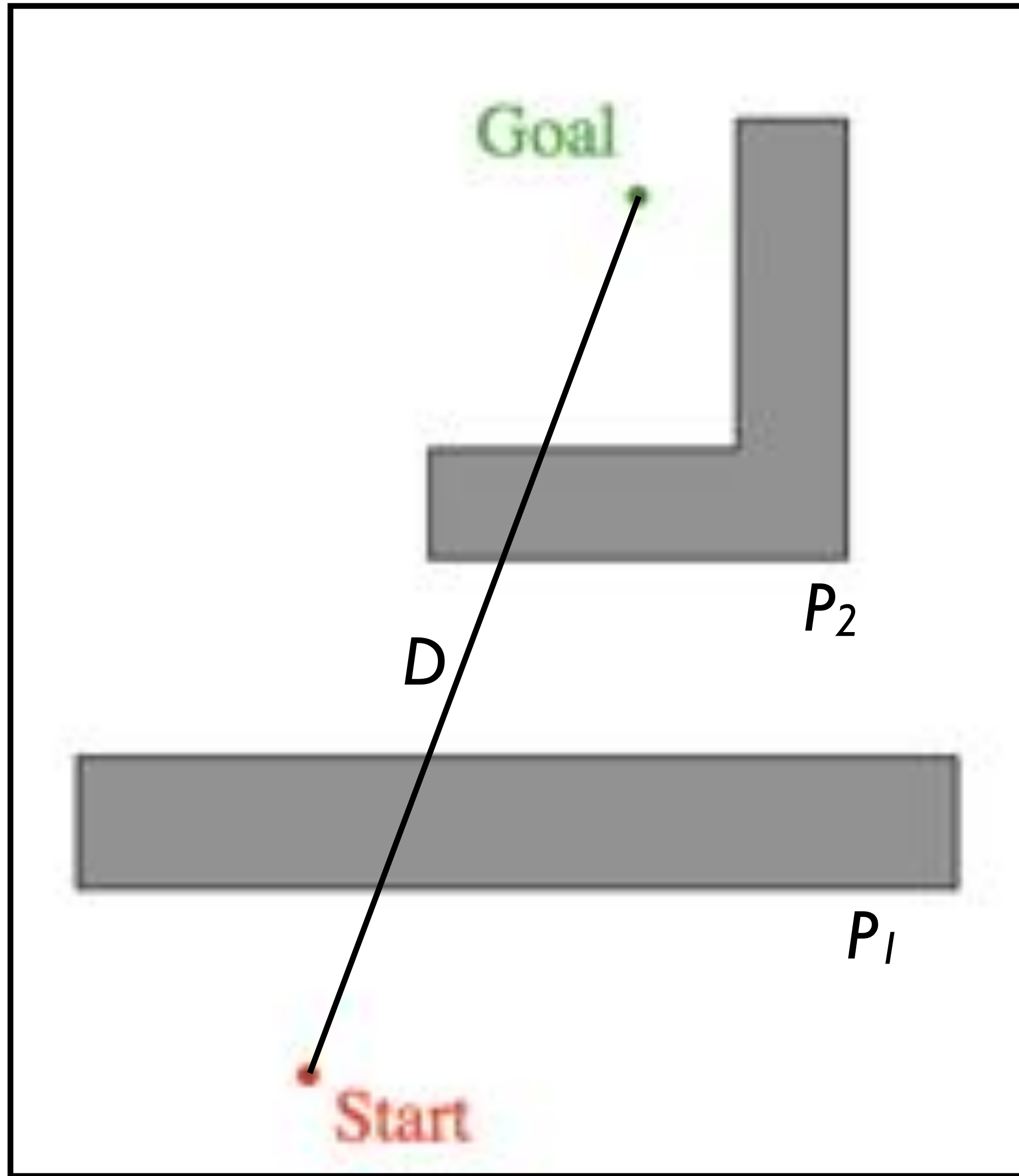


Worst case:





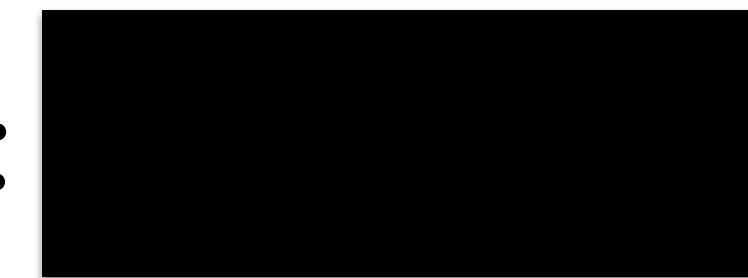
# Bug 1: Search Bounds



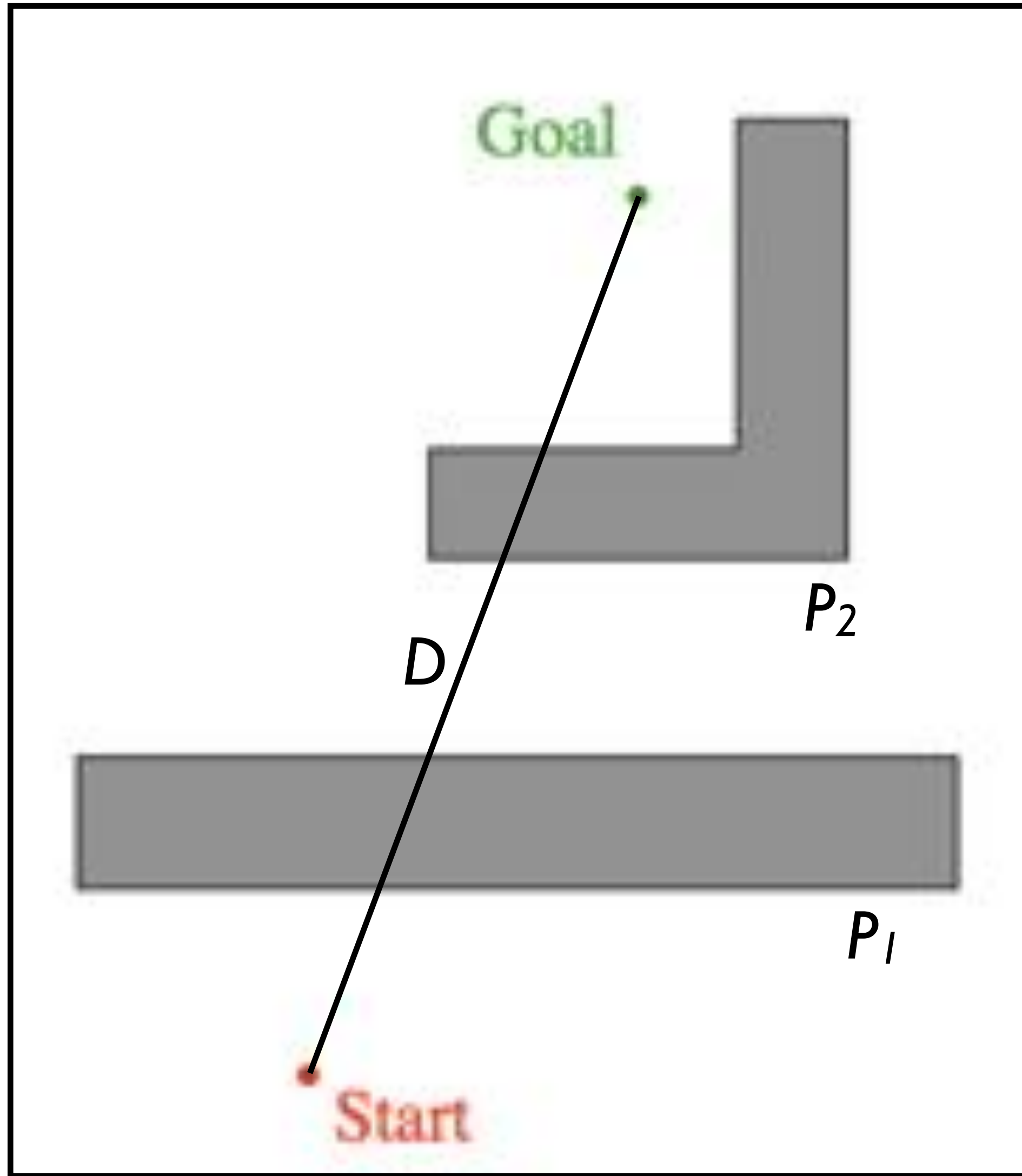
Bounds on path distance, assuming  
 $D$ : distance start-to-goal  
 $P_i$ : obstacle perimeter

Best case:  $D$

Worst case:



# Bug 1: Search Bounds



Bounds on path distance, assuming  
 $D$ : distance start-to-goal  
 $P_i$ : obstacle perimeter

Best case:  $D$

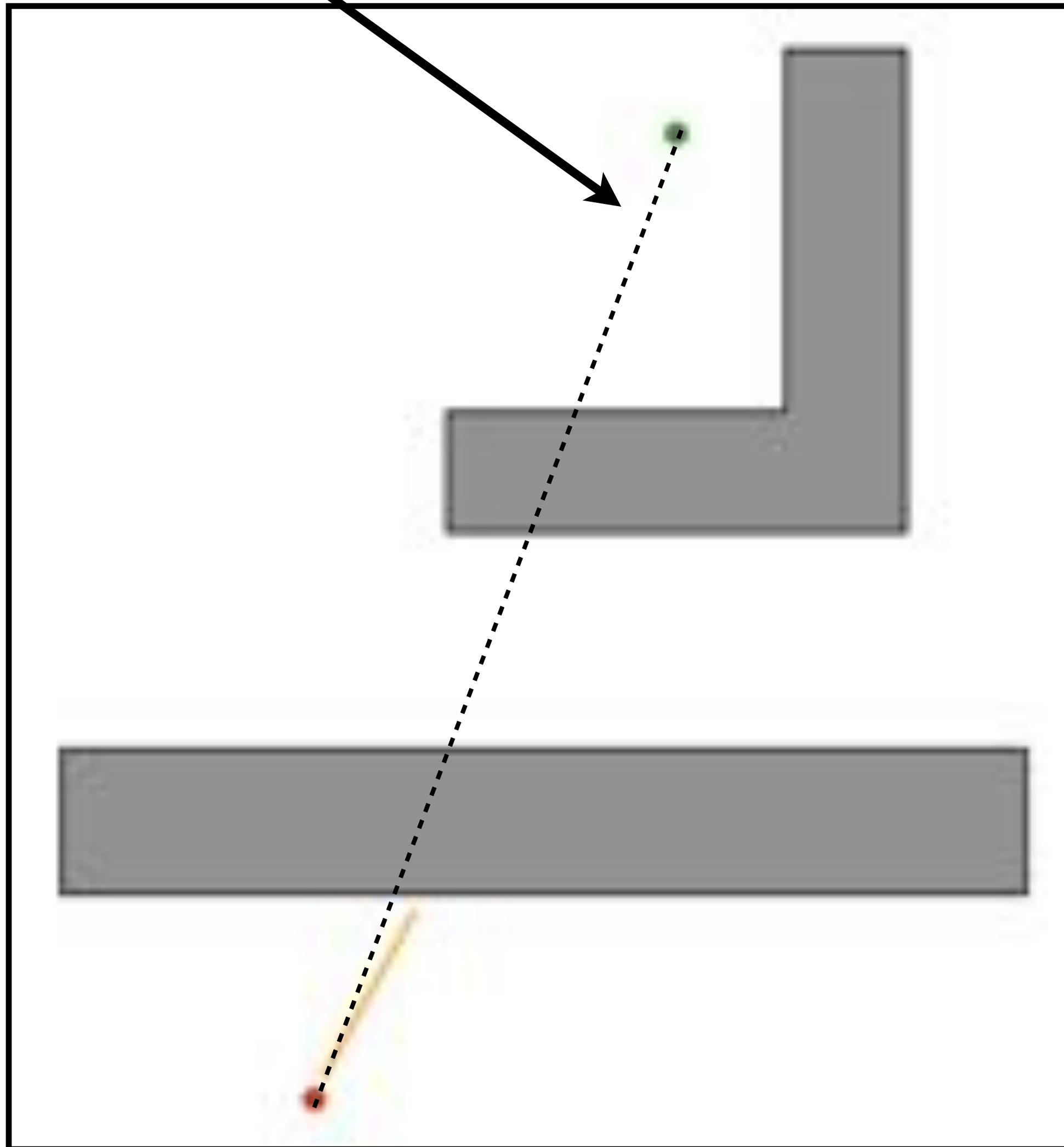
Worst case:  $D + 1.5 \sum_i P_i$

Is there a faster bug?



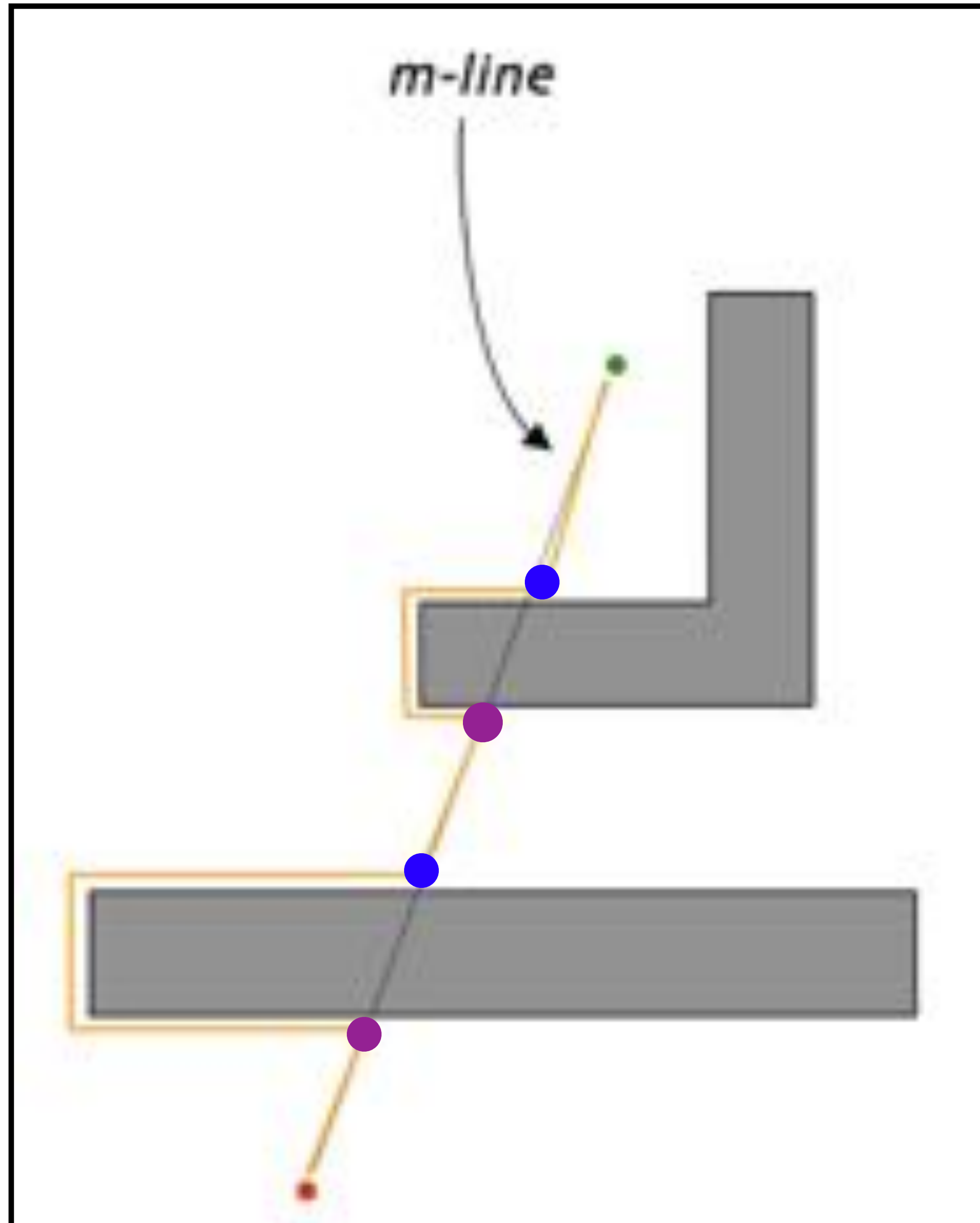
# Bug 2

**m-line:** straight line path to goal



- 1) Head towards goal on m-line
- 2) When hit point set, traverse obstacle until m-line is encountered
- 3) set leave point and exit obstacle
- 4) continue from (1)

# Bug 2

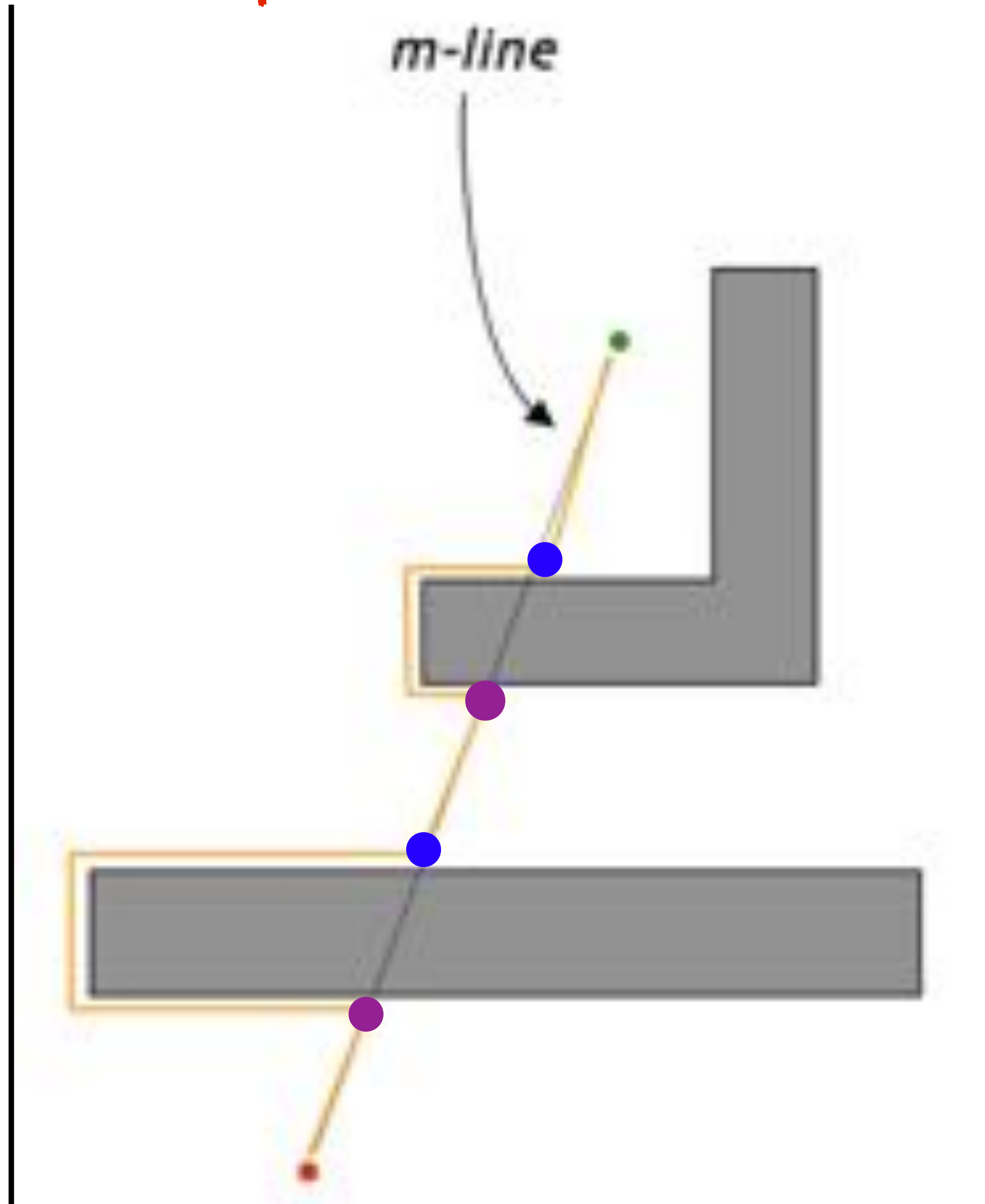


- 1) Head towards goal on m-line
- 2) When hit point set, traverse obstacle until m-line is encountered
- 3) set leave point and exit obstacle
- 4) continue from (1)



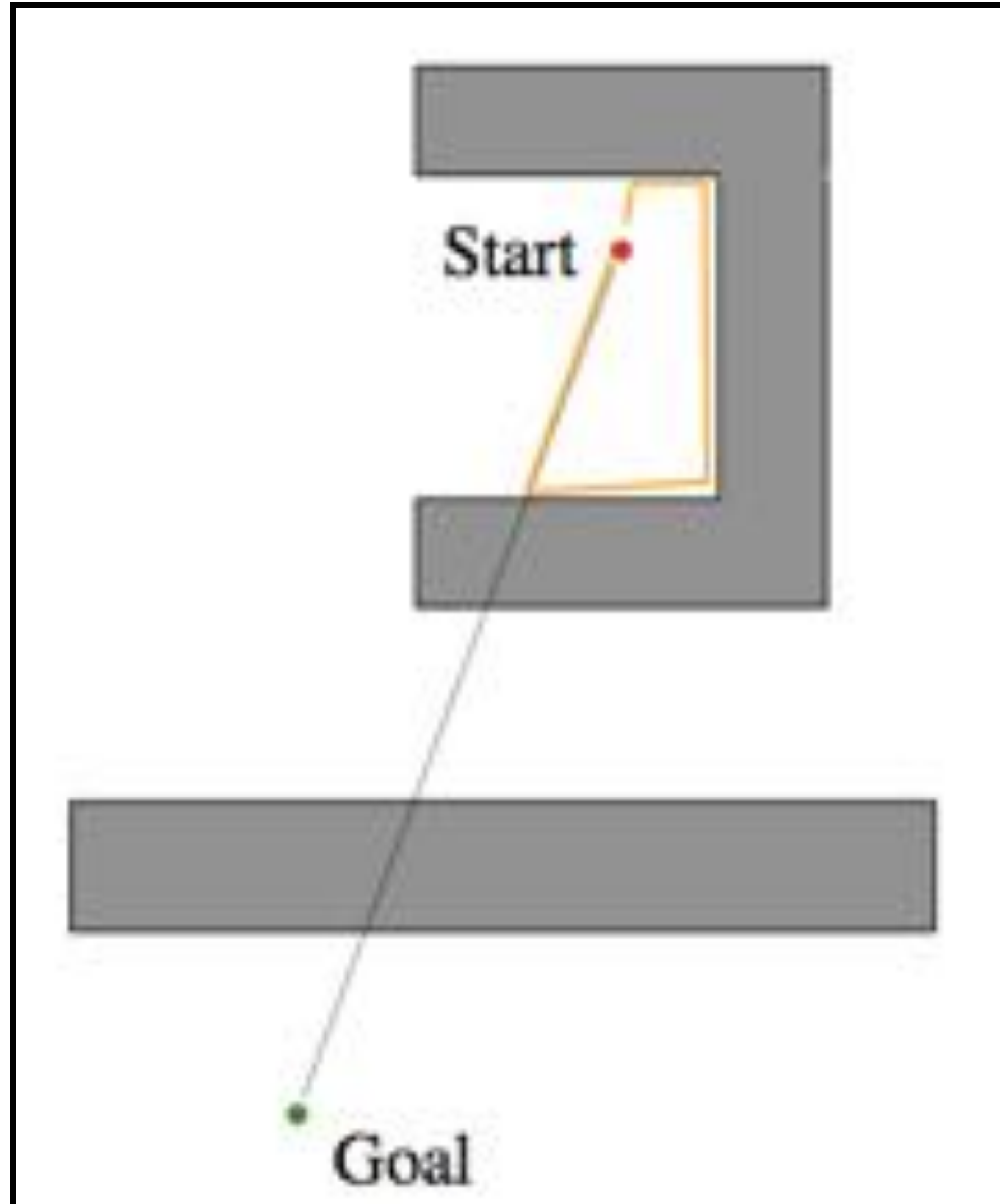
## What map would foil Bug 2?

# Bug 2



- 1) Head towards goal on m-line
- 2) When hit point set, traverse obstacle until m-line is encountered
- 3) set leave point and exit obstacle
- 4) continue from (1)

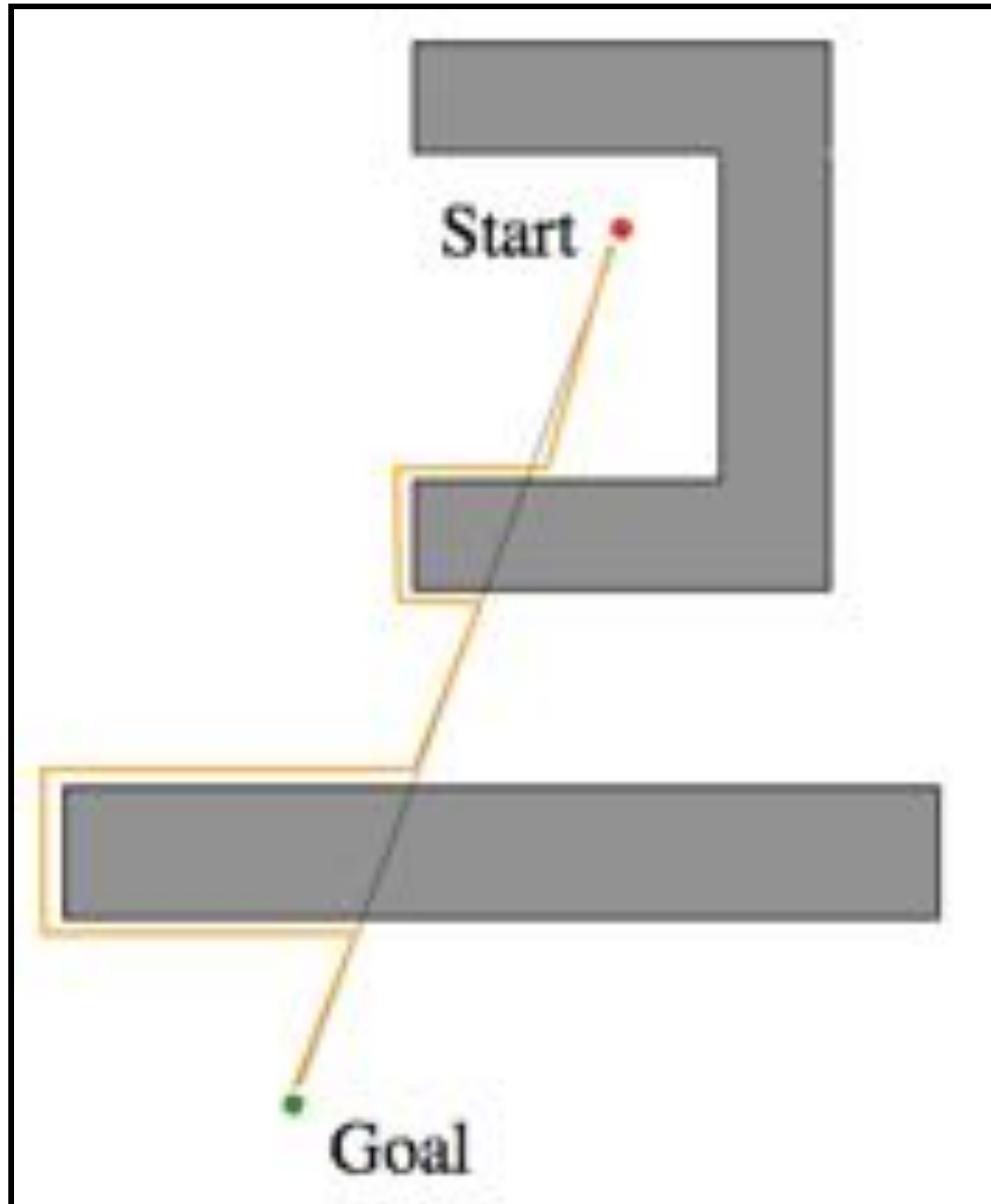
# Bug 2



- 1) Head towards goal on m-line
- 2) When hit point set, traverse obstacle until m-line is encountered
- 3) set leave point and exit obstacle
- 4) continue from (1)



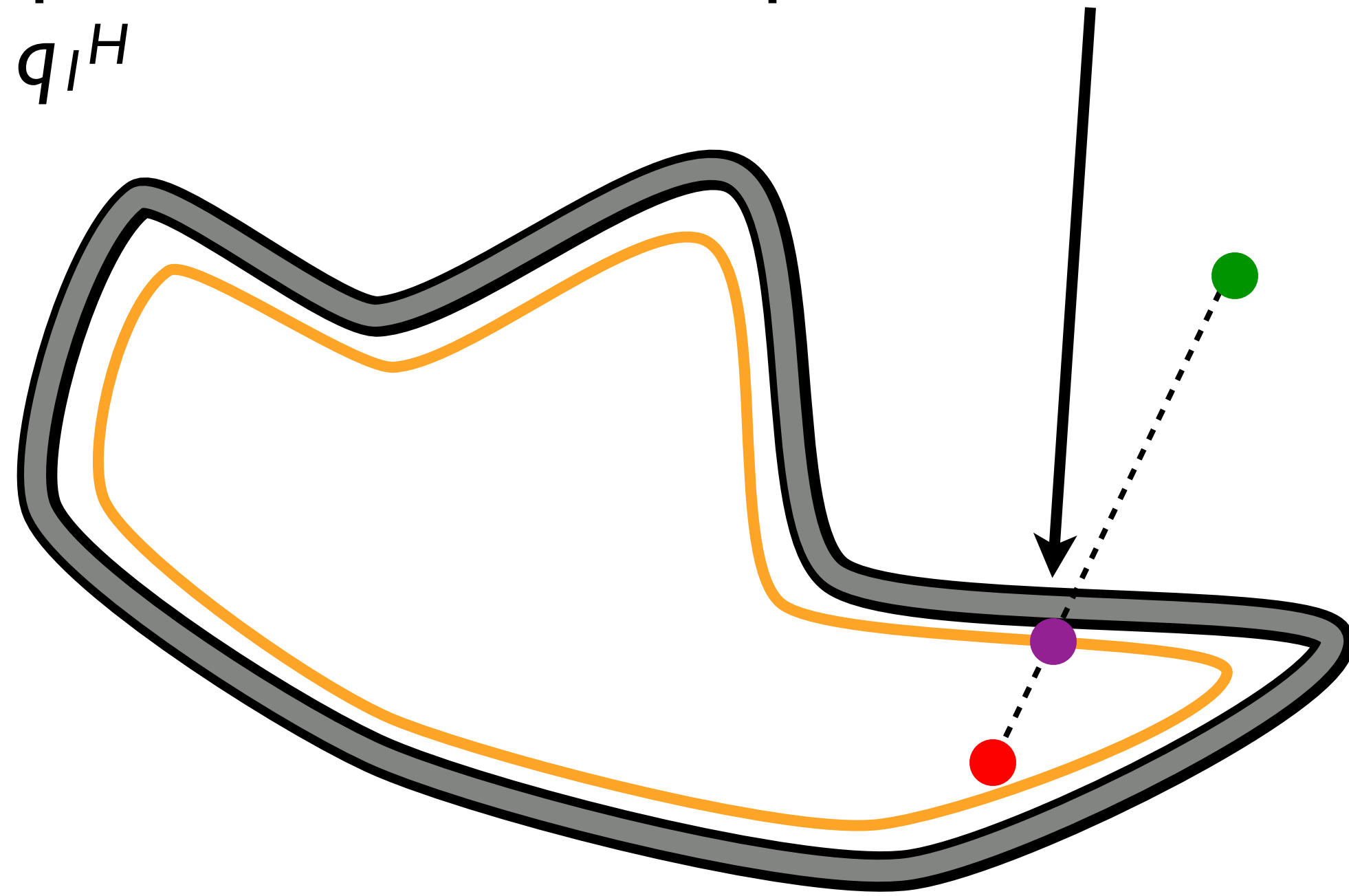
# Bug 2



- 1) Head towards goal on m-line
- 2) When hit point set, traverse obstacle until m-line is encountered  
**& closer to the goal**
- 3) set leave point and exit obstacle
- 4) continue from (1)

# Bug 2: Detecting Failure

no path exists: no leave point before returning to  $q_I^H$

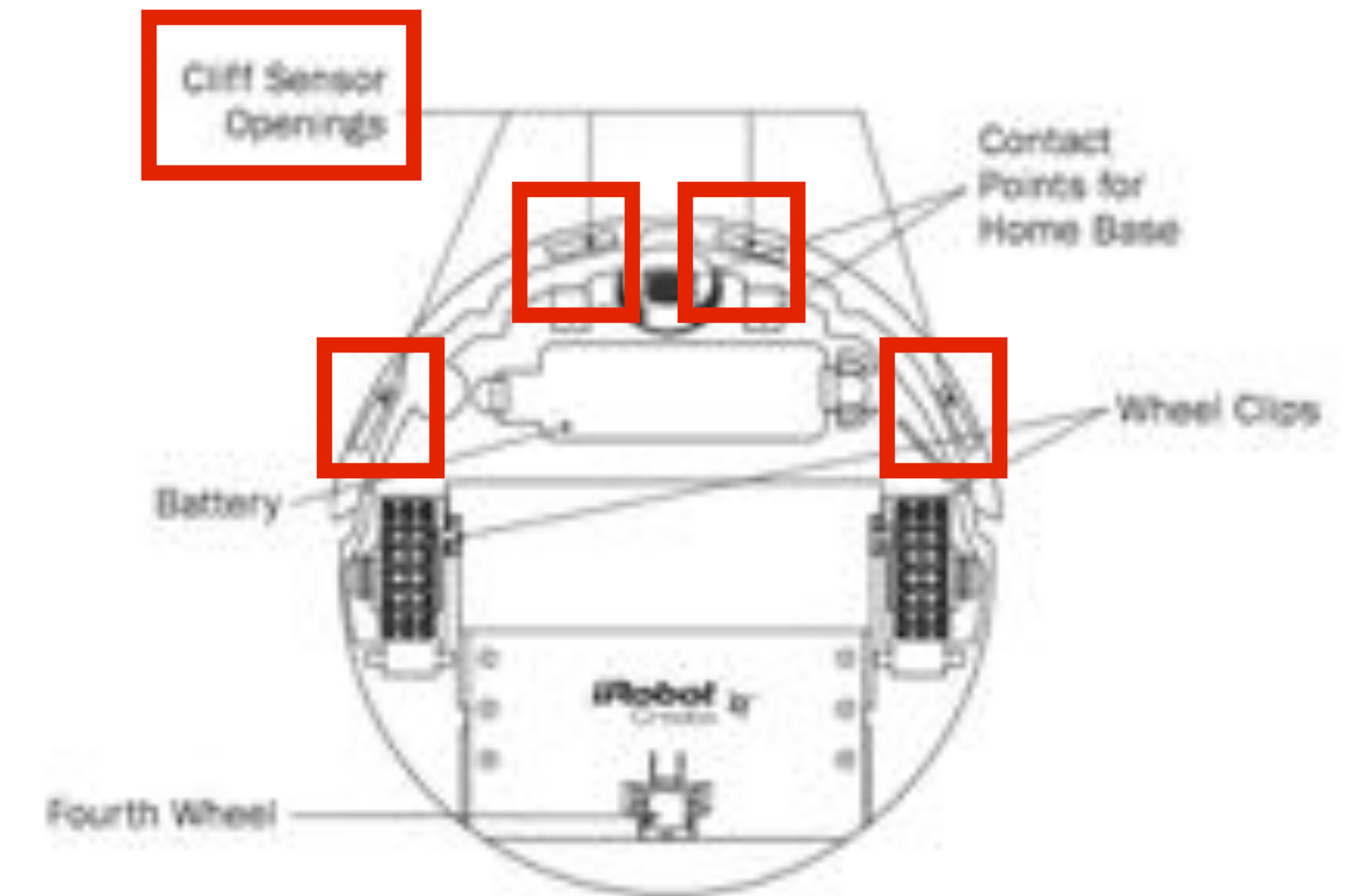


- 1) Head towards goal on m-line
- 2) When hit point set, traverse obstacle until m-line is encountered & closer to the goal  
**or hit point reached**
- 3) **if not  $i^{th}$  hit point**, set leave pt. and exit
- 4) continue from (1)

# Bug 2 in action



m-line drawn on floor  
with tape recognizable by  
Create cliff sensor



Kayle Gishen





Is Bug2 better than Bug1?



# Bug 1 v. Bug 2:

Draw worlds where Bug 2 performs better than Bug 1 (and vice versa)

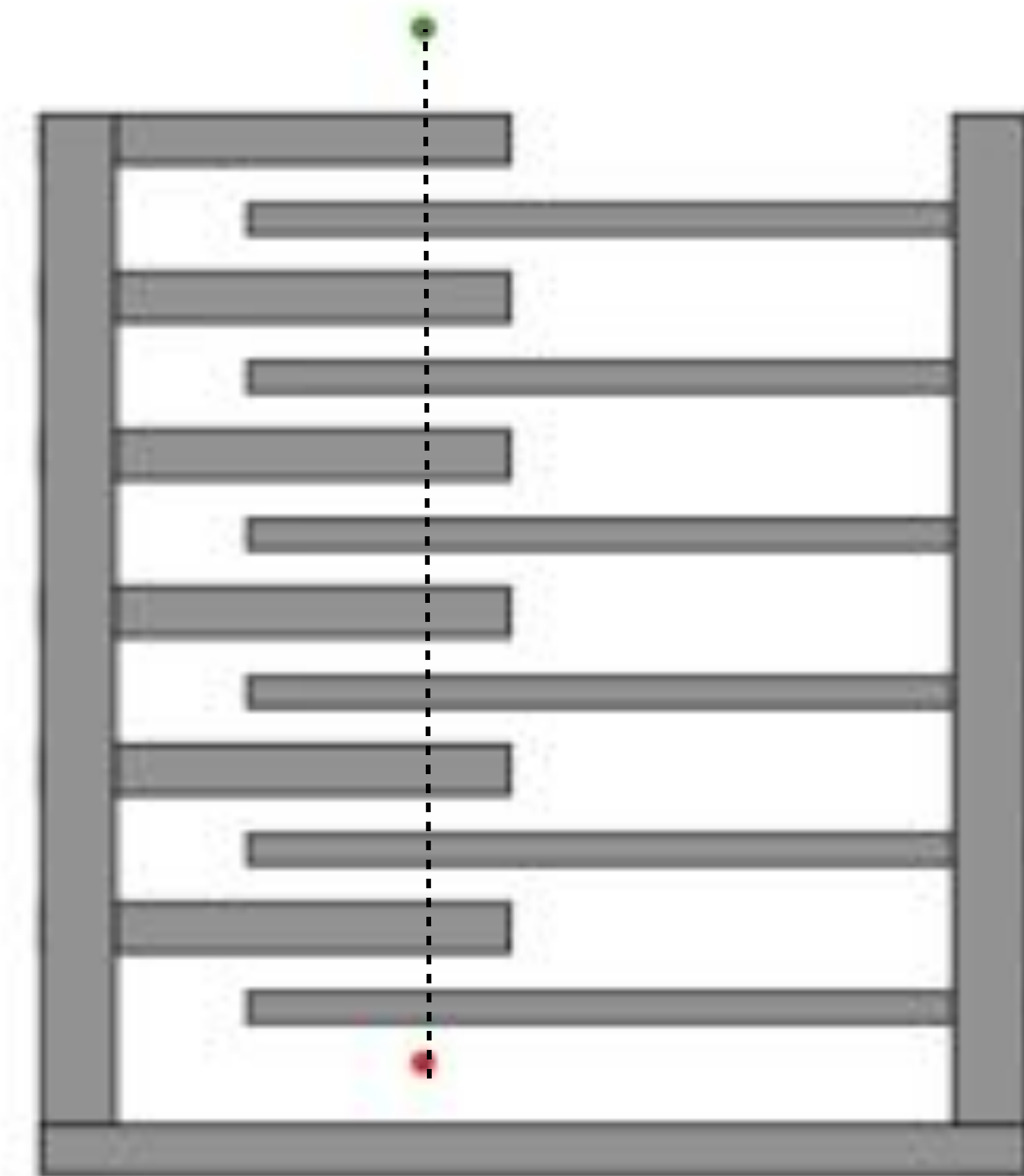
Bug 2 beats Bug 1

Bug 1 beats Bug 2

Home work!



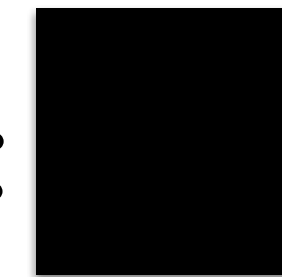
# Bug 2: Search Bounds



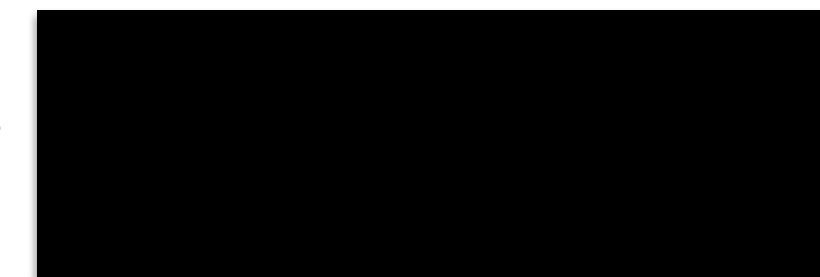
Bounds on path distance, assuming

- $D$ : distance start-to-goal
- $P_i$ : obstacle perimeter
- $n_i$ : number of m-line intersections for  $WO_i$

Best case:



Worst case:





# Bug 2: Search Bounds

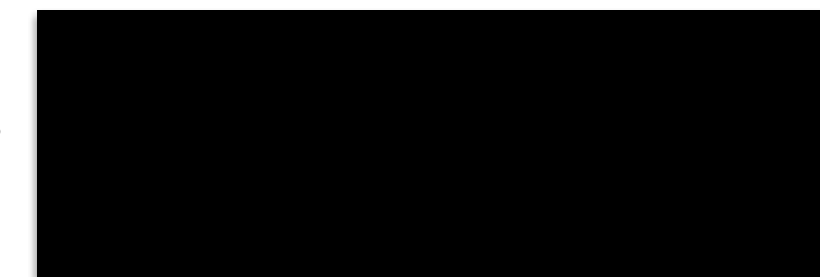


Bounds on path distance, assuming

- $D$ : distance start-to-goal
- $P_i$ : obstacle perimeter
- $n_i$ : number of m-line intersections for  $WO_i$

Best case:  $D$

Worst case:



# Bug 2: Search Bounds



Bounds on path distance, assuming

- $D$ : distance start-to-goal
- $P_i$ : obstacle perimeter
- $n_i$ : number of m-line intersections for  $WO_i$

Best case:  $D$

Worst case:  $D + \sum_i (n_i/2)P_i$

Why?

Why?

Consider all leave points on m-line;  
only half are valid



# Bug 2:

## Search Bounds

Bounds on path distance, assuming

- $D$ : distance start-to-goal
- $P_i$ : obstacle perimeter
- $n_i$ : number of m-line intersections for  $WO_i$

Best case:  $D$

Worst case:  $D + \sum_i (n_i/2)P_i$

Each leave pt might require traversing entire  
obstacle perimeter, including the outside



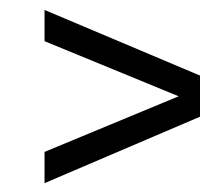
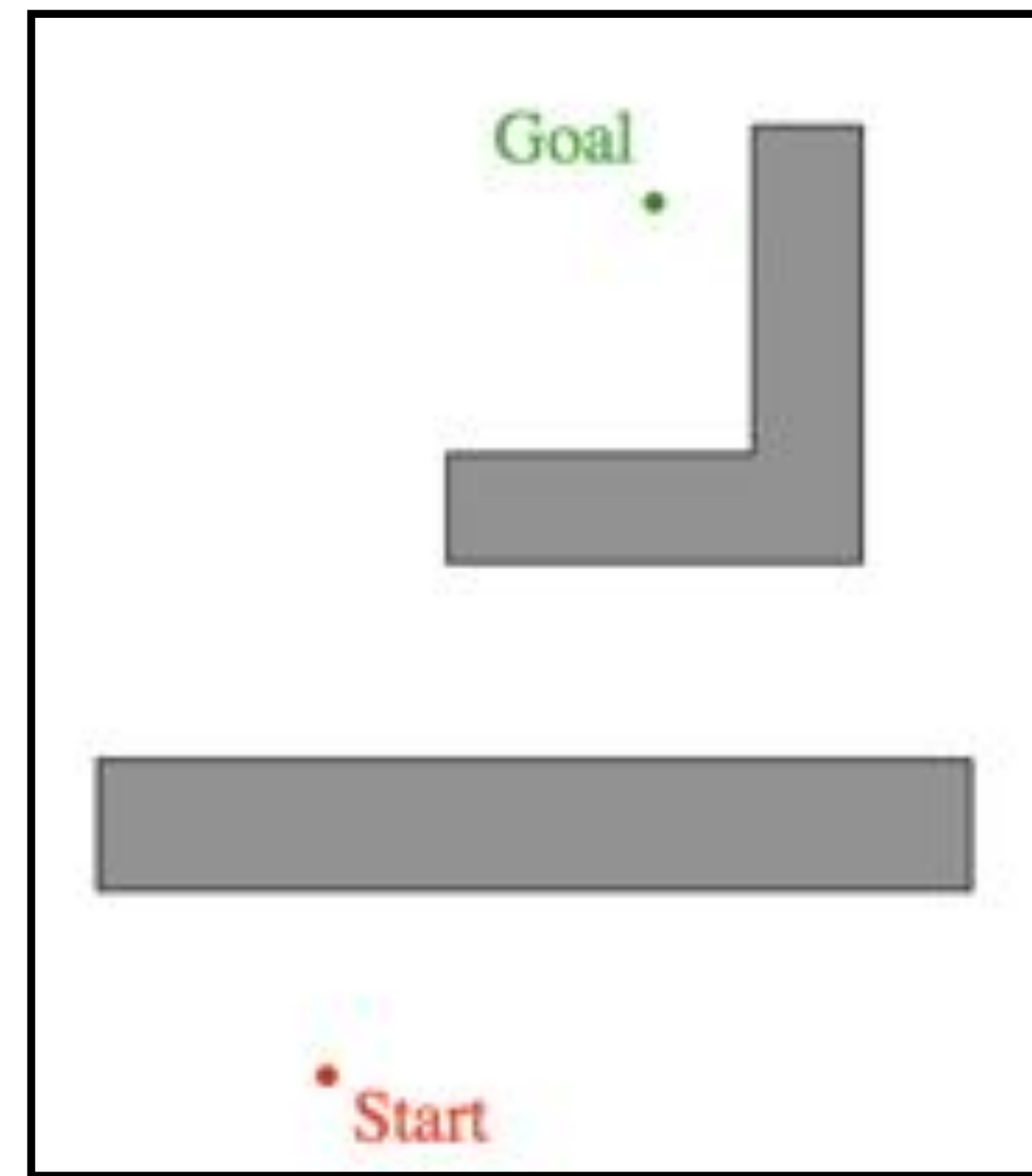
Suppose robot has a range sensor.

Is there a better Bug algorithm?



# Tangent Bug

- Assume bounded world
- Known: global goal
  - measurable distance  $d(x,y)$
- Local sensing
  - **range finding**
  - odometry





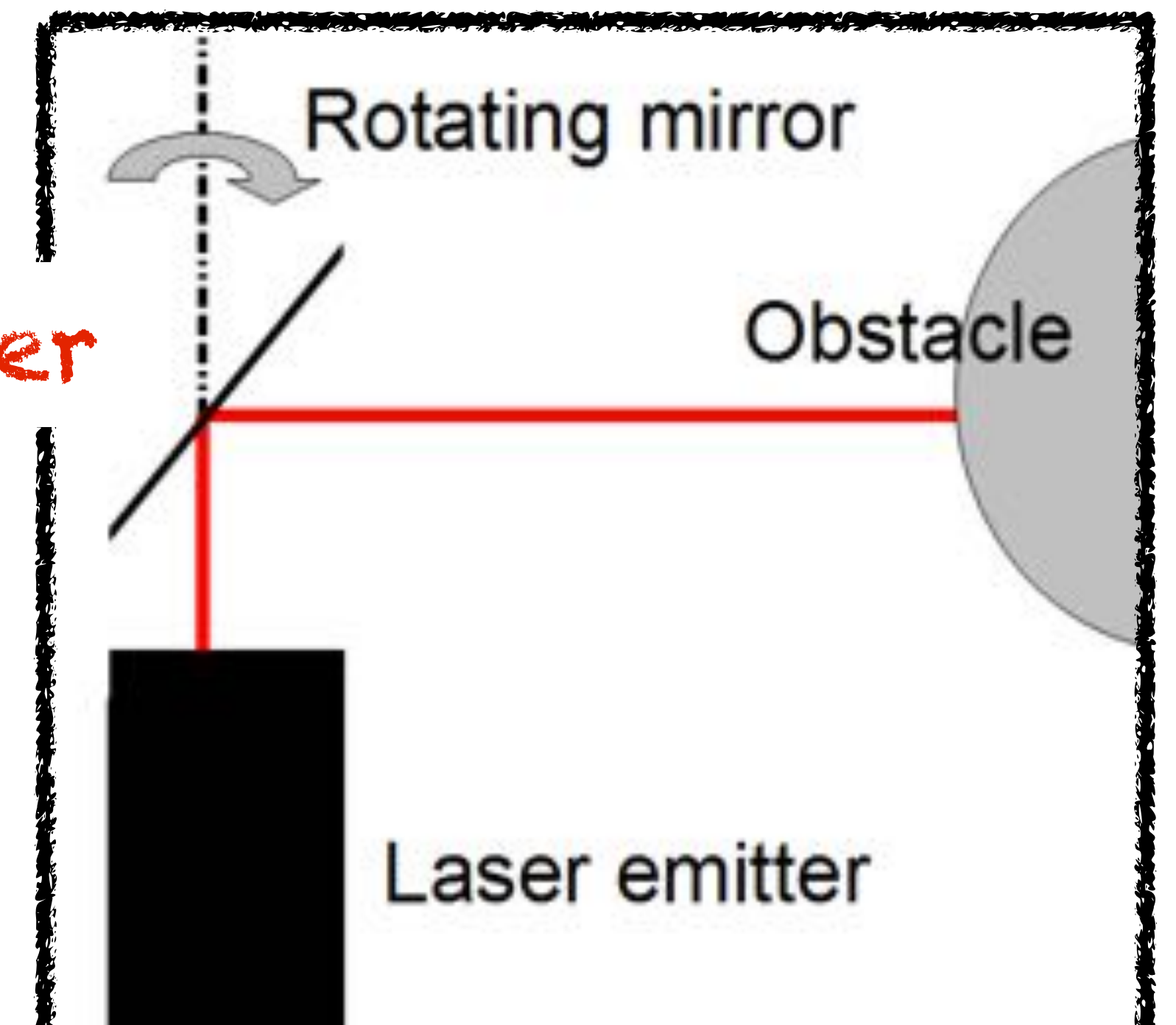
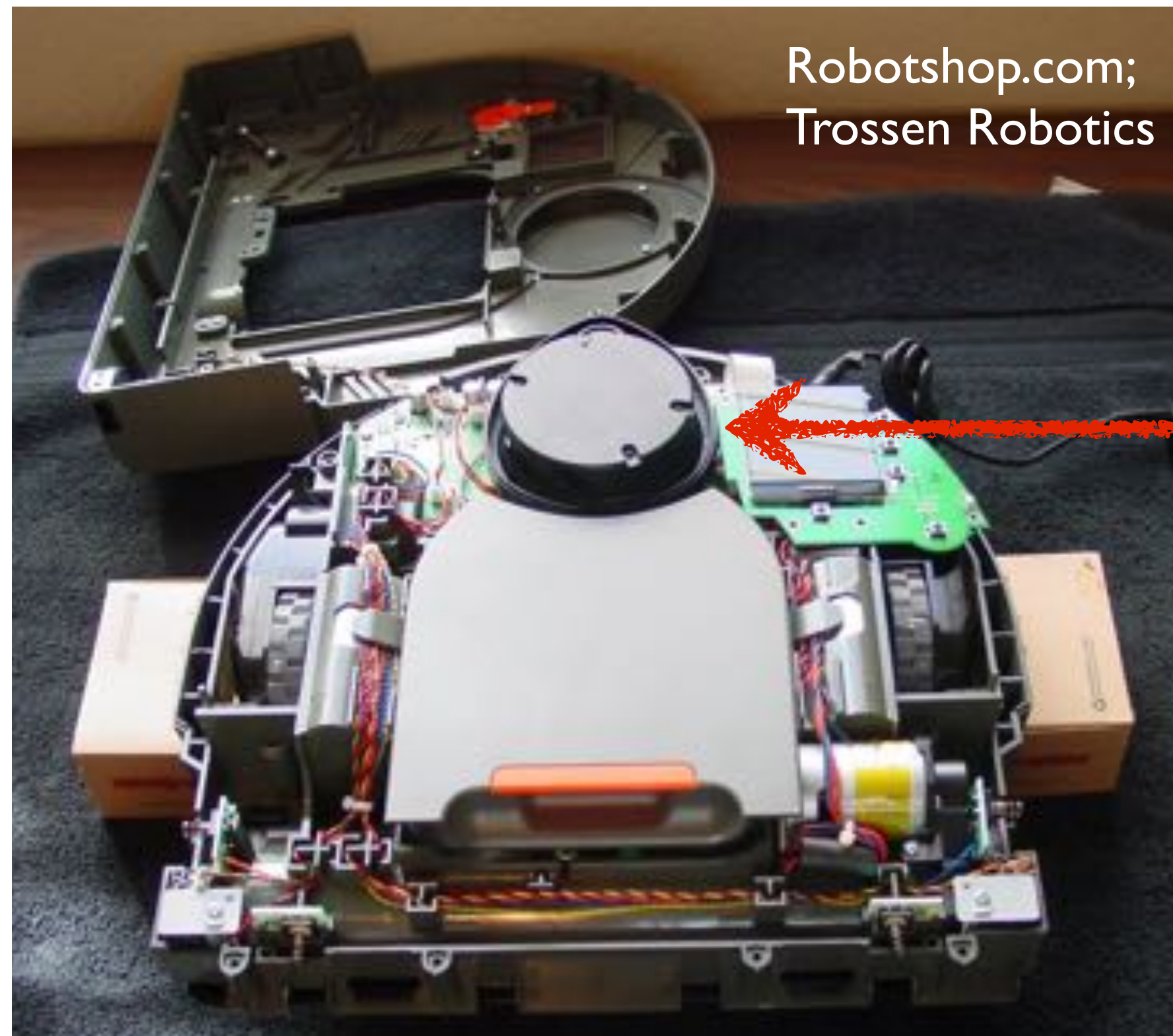
# Laser Rangefinding

(briefly)

Emit laser beam in a direction

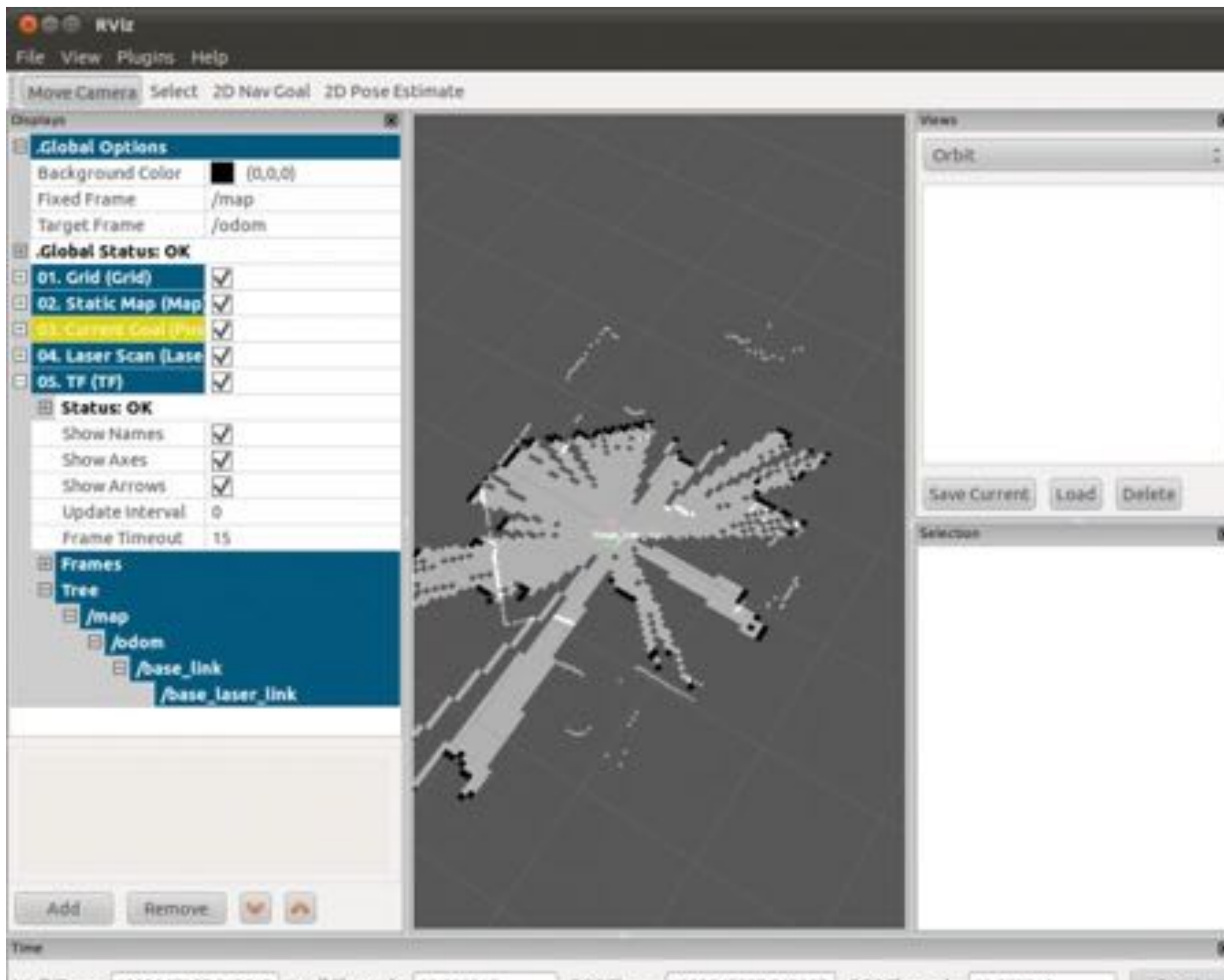
Distance to nearest object related to time from emission to sensing of beam  
(assumes speed of light is known)

Planar range finding : reflect laser on spinning mirror (typically at 10Hz)



range finder





## ROS LaserScan definition

### LaserScan message:

Header header

uint32 seq

time stamp

string frame\_id

float32 angle\_min

float32 angle\_max

float32 angle\_increment

float32 time\_increment

float32 scan\_time

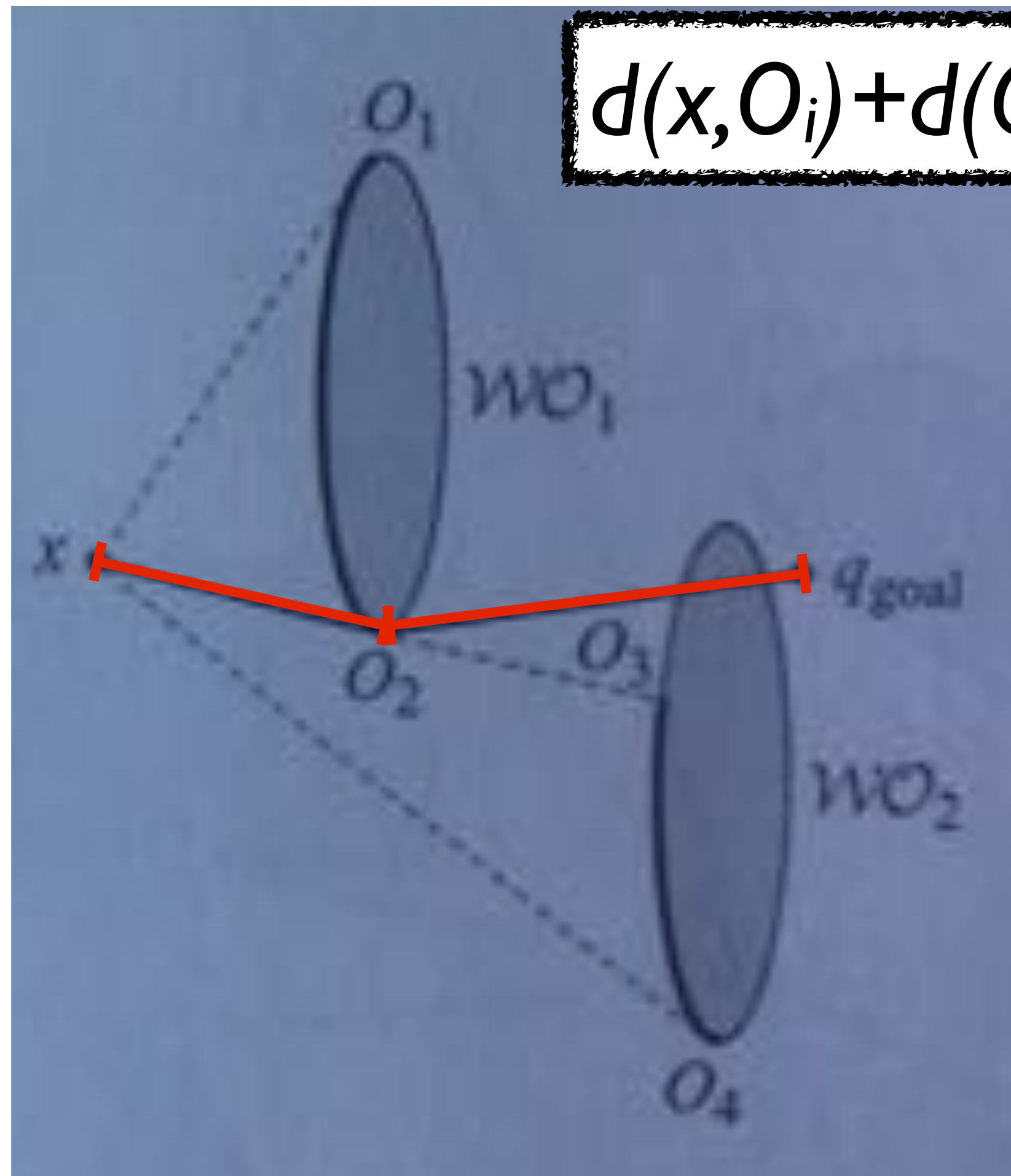
float32 range\_min

float32 range\_max

float32[] ranges

float32[] intensities

# Tangent Bug: Heuristic Distance-to-Goal



$$d(x, O_i) + d(O_i, q_{goal})$$

$O_i$  are visible obstacle extents

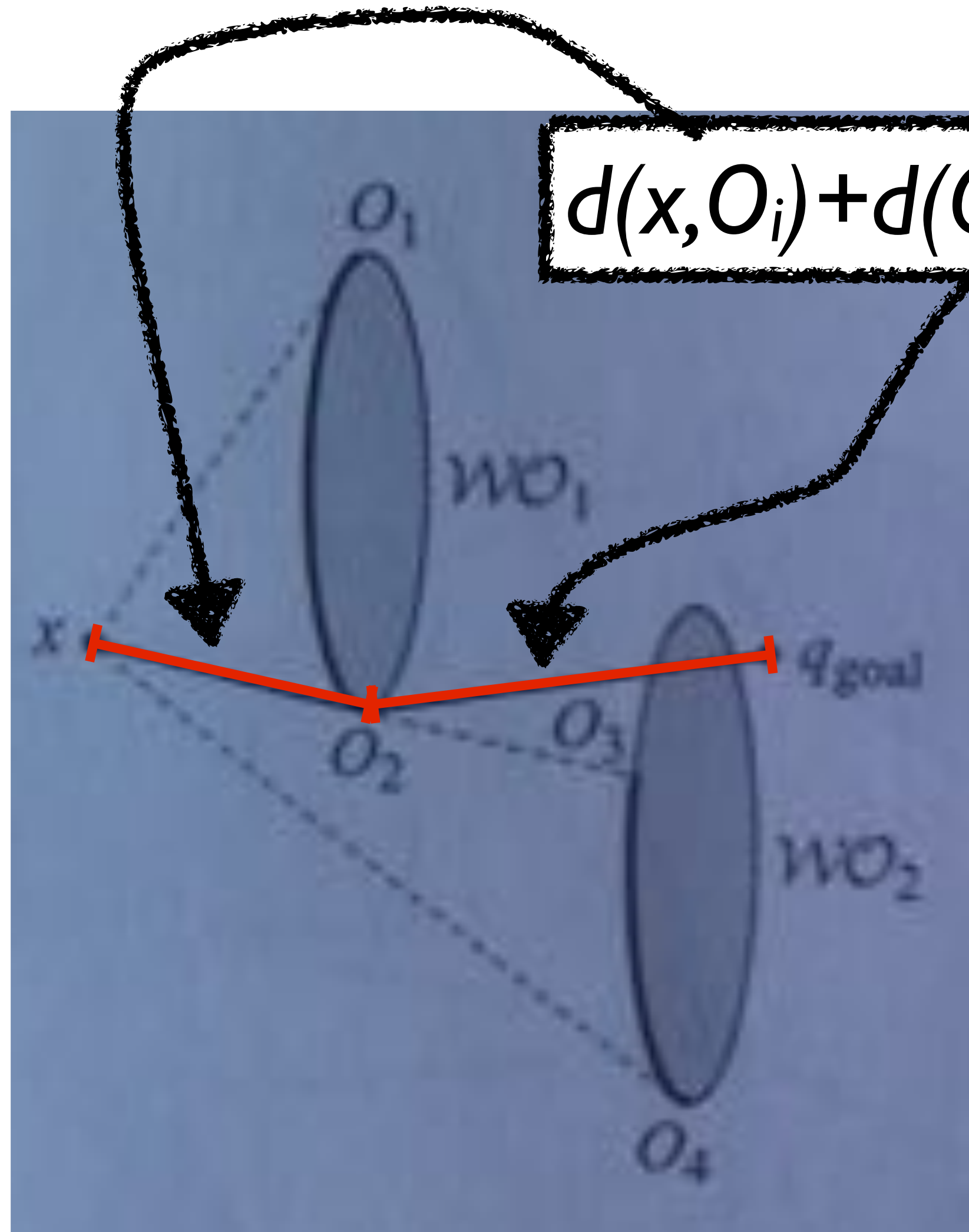
$d(x, O_i)$ : robot can see

$d(O_i, q_{goal})$ : best path robot cannot see

Continually move robot such that distance to goal is decreased

Note similarity to  $A^*$  search heuristic

# Tangent Bug: Heuristic Distance-to-Goal



$O_i$  are visible obstacle extents

$d(x, O_i)$ : robot can see

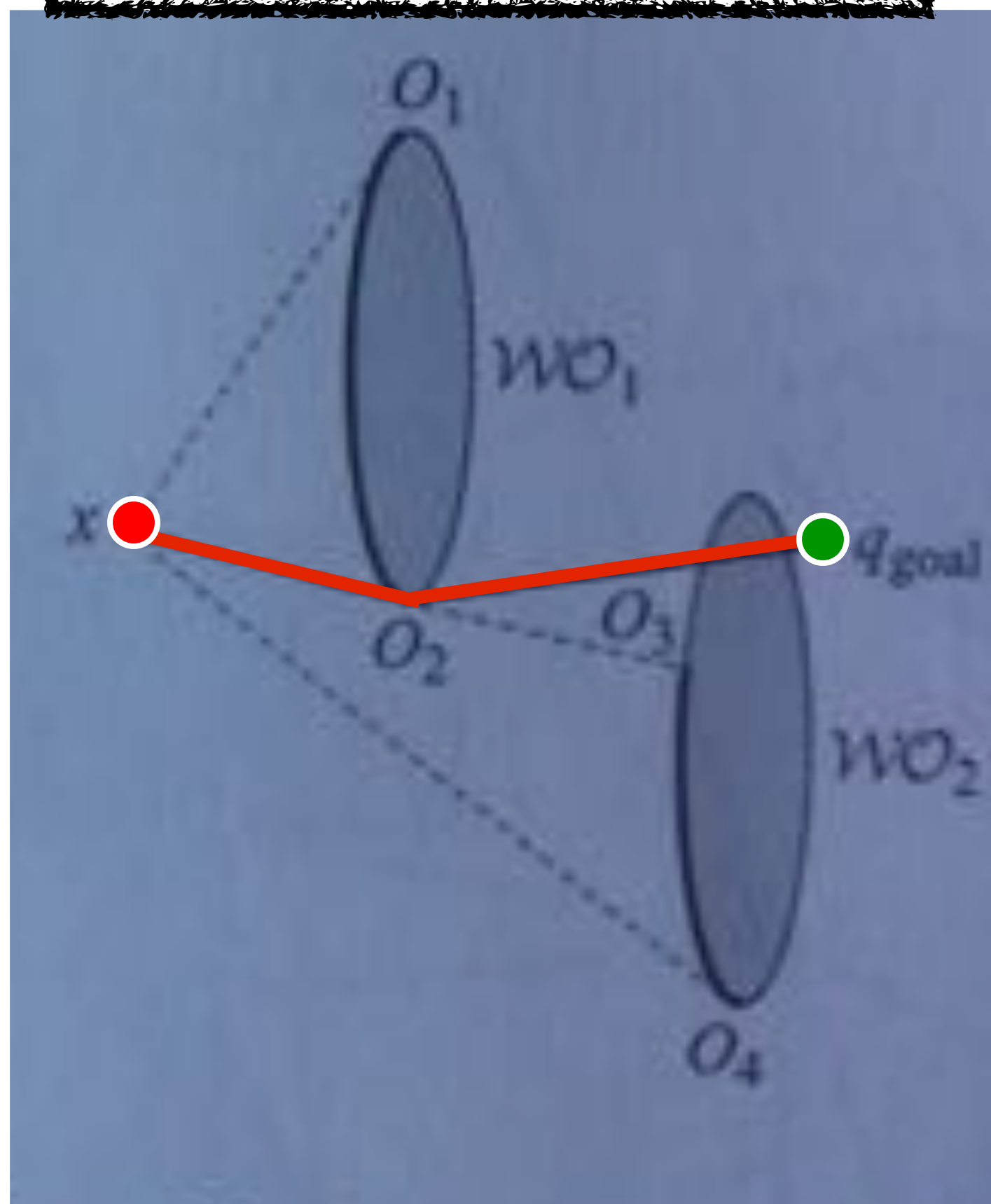
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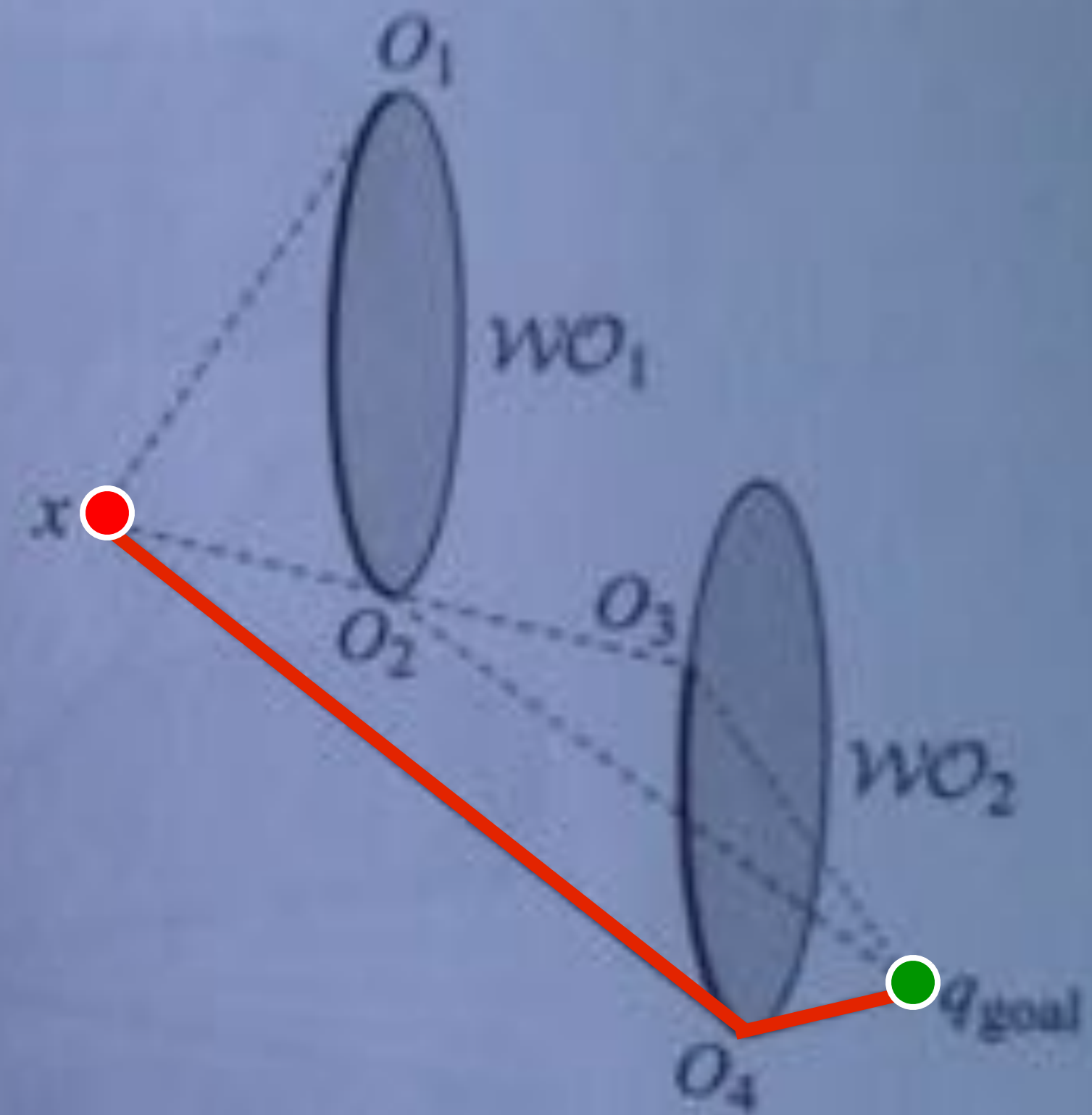
Note similarity to  $A^*$  search heuristic



$$d(x, O_2) + d(O_2, q_{\text{goal}})$$



$$d(x, O_4) + d(O_4, q_{\text{goal}})$$

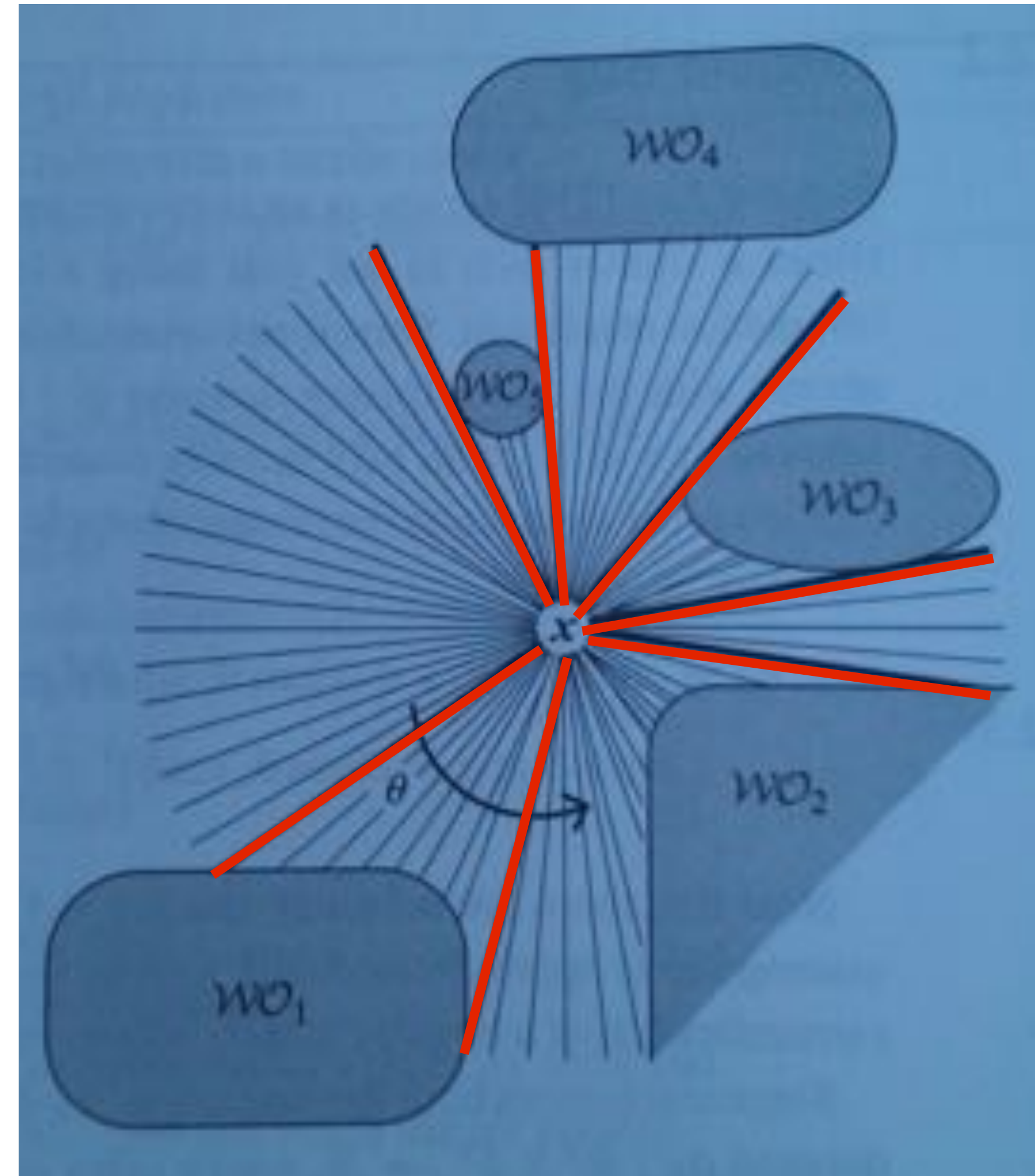


# Range Segmentation

range scan  $\rho(x, \Theta)$ : sensed distance along ray at angle  $\Theta$  within limit  $R$

discontinuities  $\{O_i\}$  in scan result from obstacles

$\{O_i\}$  segments scan into intervals continuity, with obstacles and free space



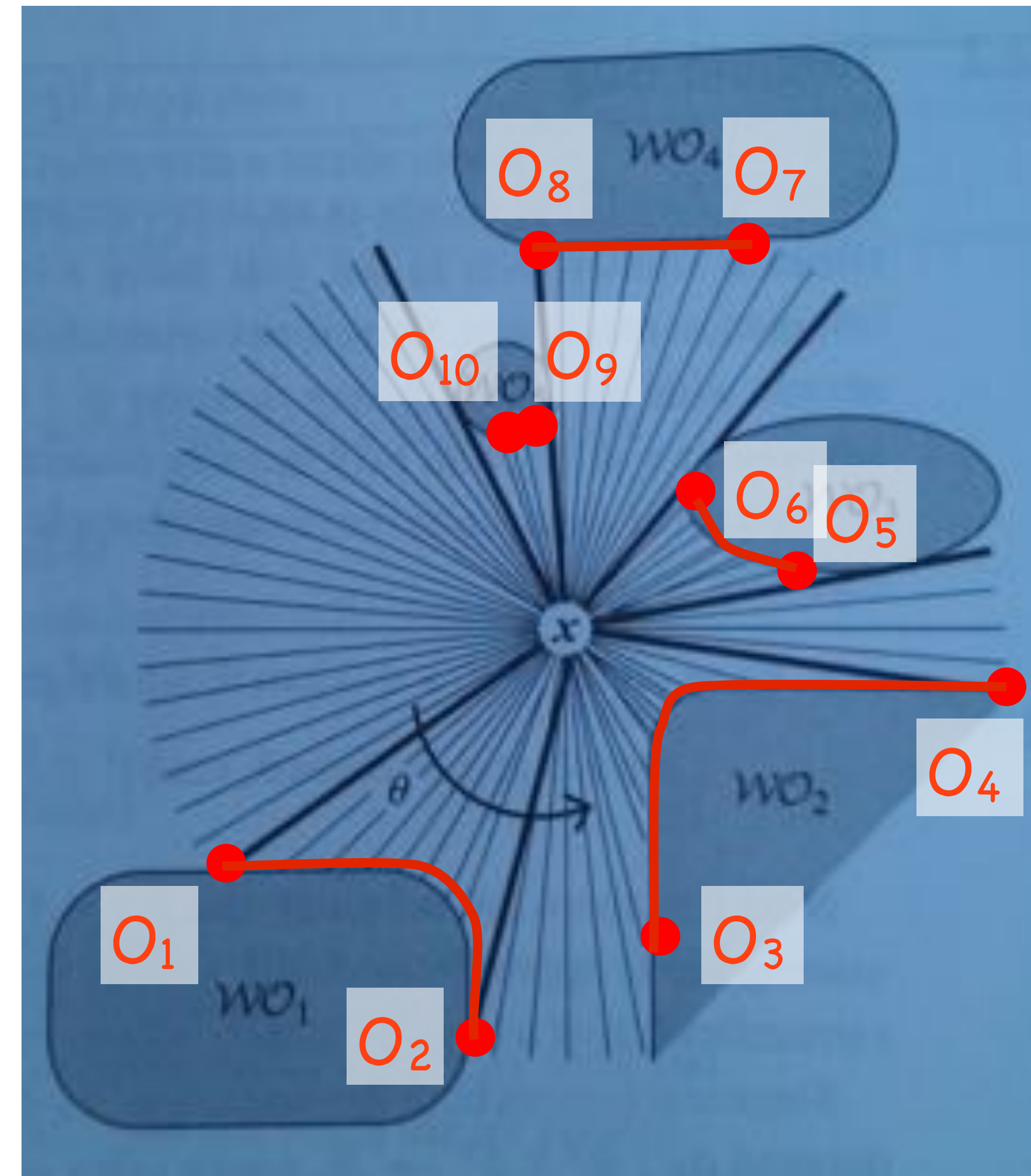


# Range Segmentation

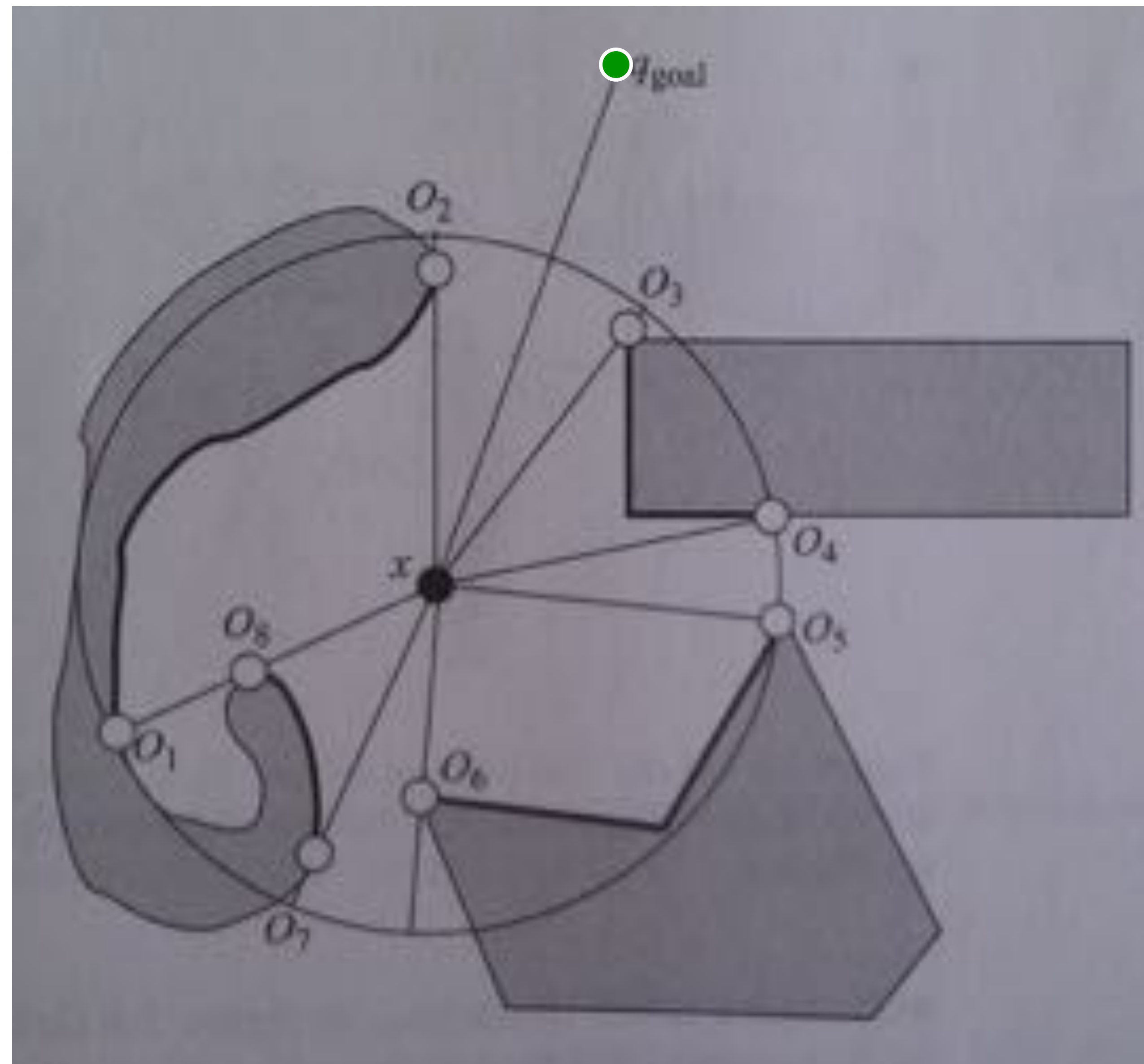
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discontinuities  $\{O_i\}$  in scan result from obstacles

$\{O_i\}$  segments scan into intervals continuity, with obstacles and free space

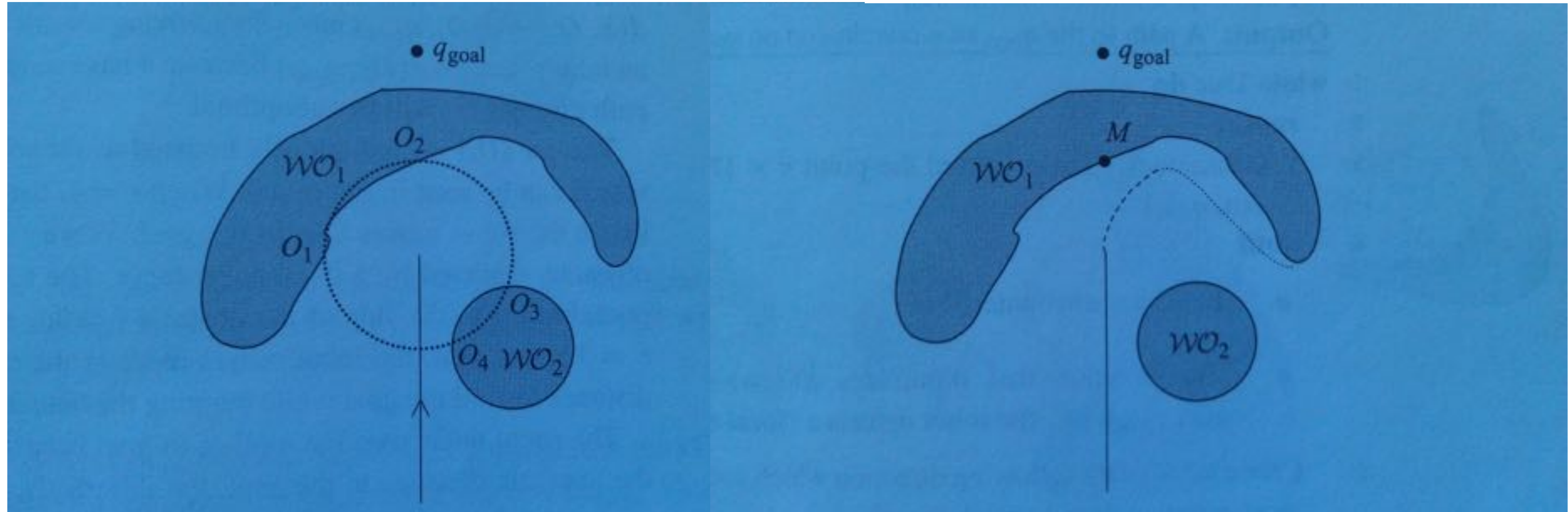






# Tangent Bug Behaviors

Similar to other bug algorithms, Tangent Bug uses two behaviors:

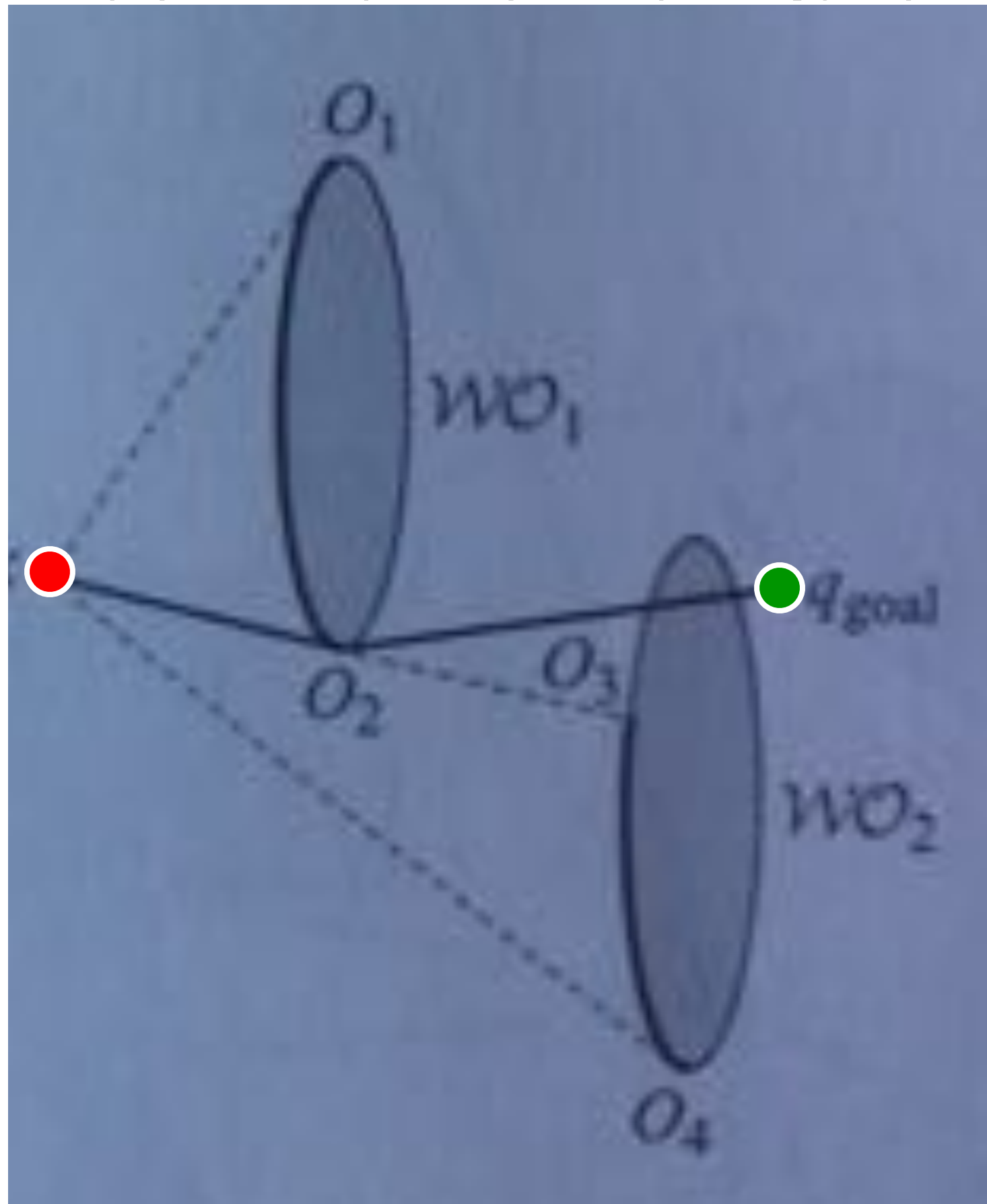


motion-to-goal

boundary-follow

# Tangent Bug

$$G(x) = d(x, O_i) + d(O_i, q_{goal})$$



1) motion-to-goal: Move to current  $O_i$  to minimize  $G(x)$ , until goal (success) or  $G(x)$  increases (local minima)

2) boundary-follow: move in while loop:

a) repeat updates

$$d_{reach} = \min d(q_{goal}, \{\text{visible } O_i\})$$

$$d_{follow} = \min d(q_{goal}, \text{sensed}(WO_j))$$

$$O_i = \operatorname{argmin}_i d(x, O_i) + d(O_i, q_{goal})$$

b) until

goal reached, (**success**)

robot cycles around obstacle, (**fail**)

$$d_{reach} < d_{follow},$$

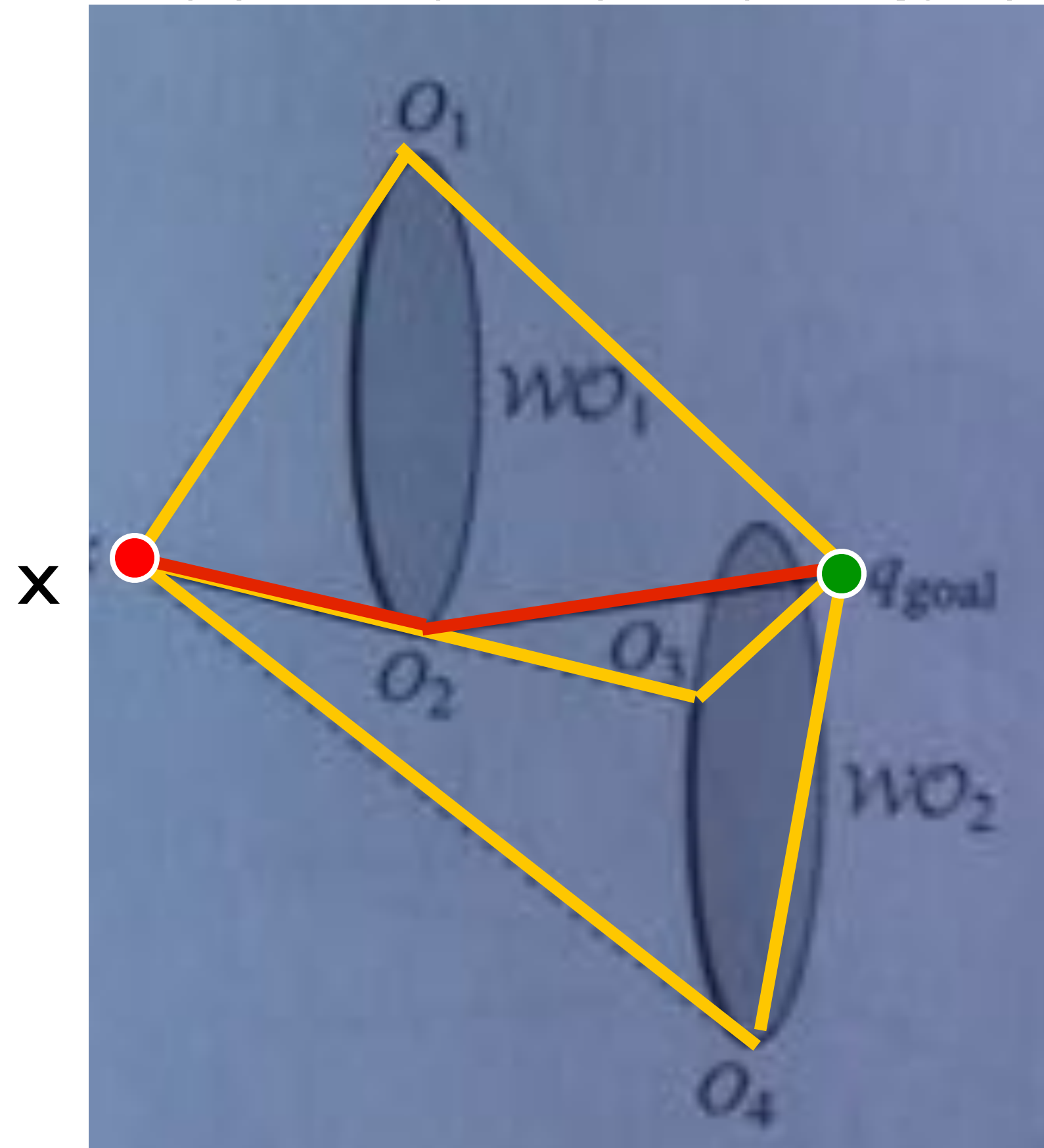
(**cleared obstacle or local minima**)

3) continue from (1)



# Tangent Bug

$$G(x) = d(x, O_2) + d(O_2, q_{goal})$$



min  $G(x)$  in red, others in yellow

1) motion-to-goal: Move to current  $O_i$  to minimize  $G(x)$ , until goal (success) or  $G(x)$  increases (local minima)

2) boundary-follow: move in while loop:

a) repeat updates

$$d_{reach} = \min d(q_{goal}, \{\text{visible } O_i\})$$

$$d_{follow} = \min d(q_{goal}, \text{sensed}(WO_j))$$

$$O_i = \operatorname{argmin}_i d(x, O_i) + d(O_i, q_{goal})$$

b) until

goal reached, (**success**)

robot cycles around obstacle, (**fail**)

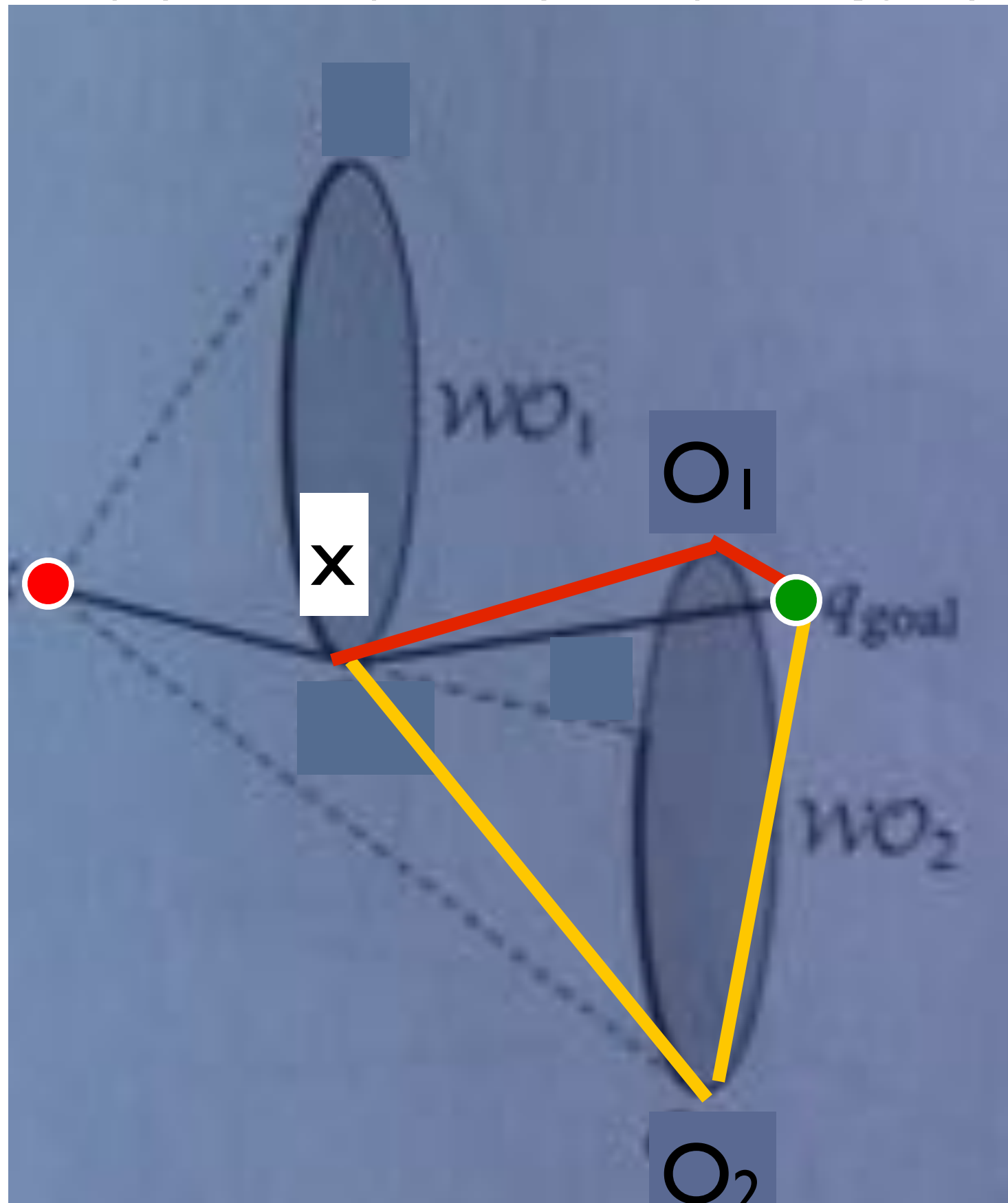
$$d_{reach} < d_{follow},$$

(**cleared obstacle or local minima**)

3) continue from (1)

# Tangent Bug

$$G(x) = d(x, O_i) + d(O_i, q_{goal})$$



min  $G(x)$  in red, others in yellow

1) motion-to-goal: Move to current  $O_i$  to minimize  $G(x)$ , until goal (success) or  $G(x)$  increases (local minima)

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$$O_i = \operatorname{argmin}_i d(x, O_i) + d(O_i, q_{goal})$$

b) until

goal reached, (**success**)

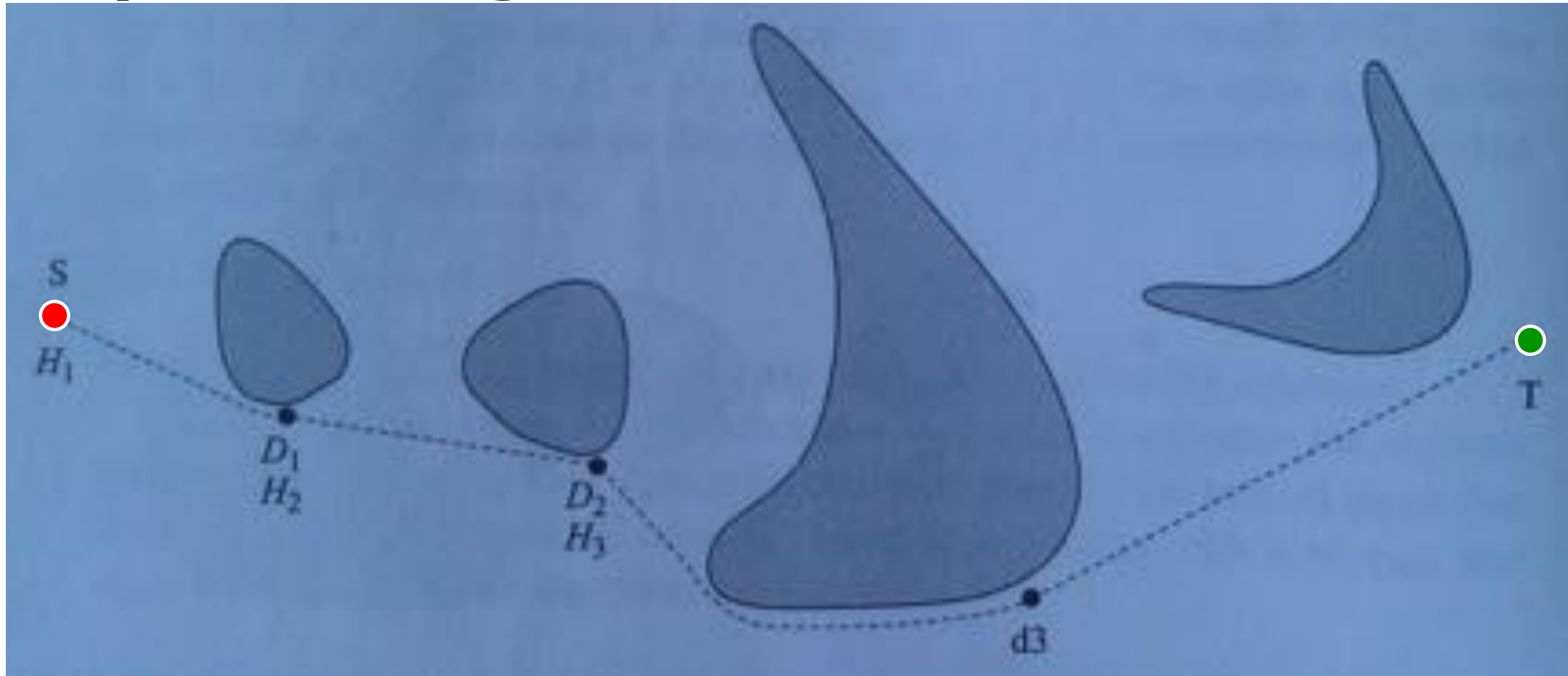
robot cycles around obstacle, (**fail**)

$$d_{reach} < d_{follow},$$

(**cleared obstacle or local minima**)

3) continue from (1)

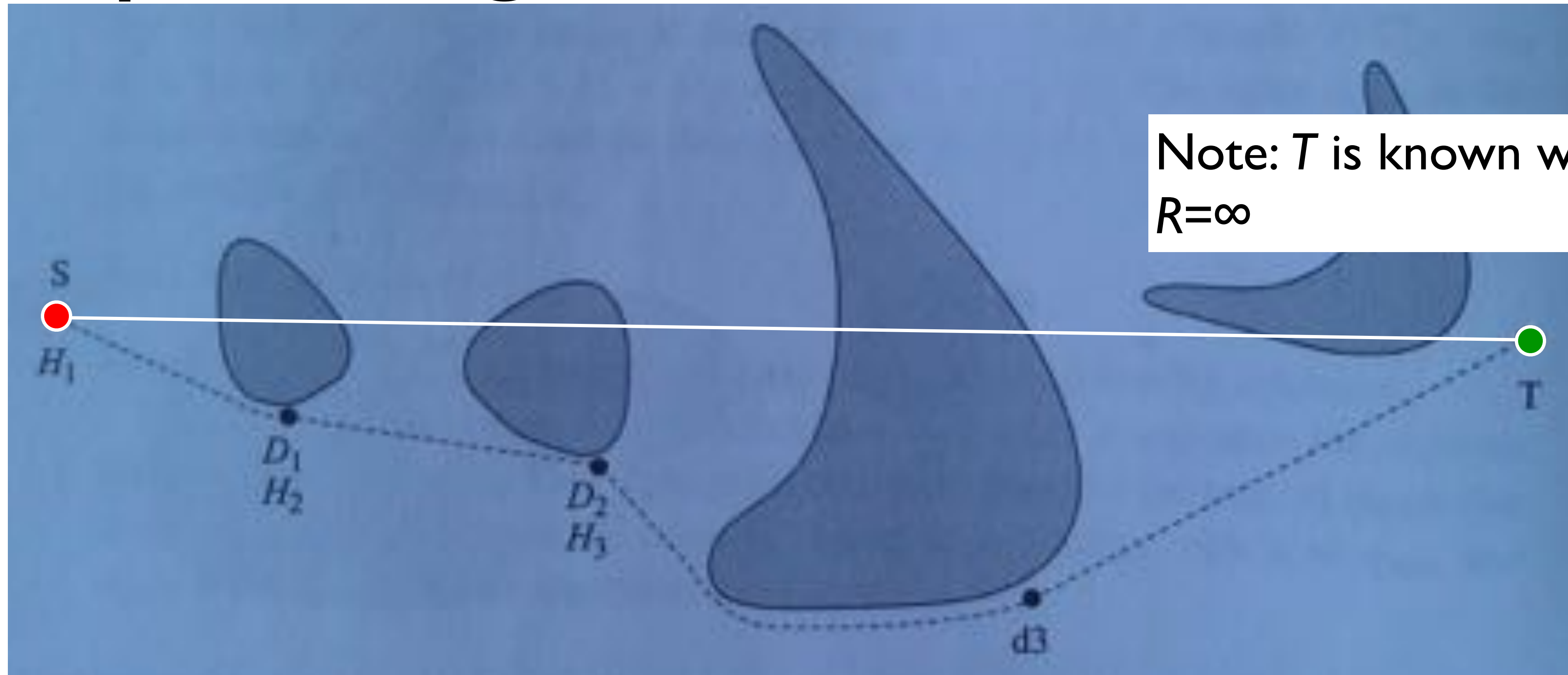
# Example: range $R=\infty$



$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima



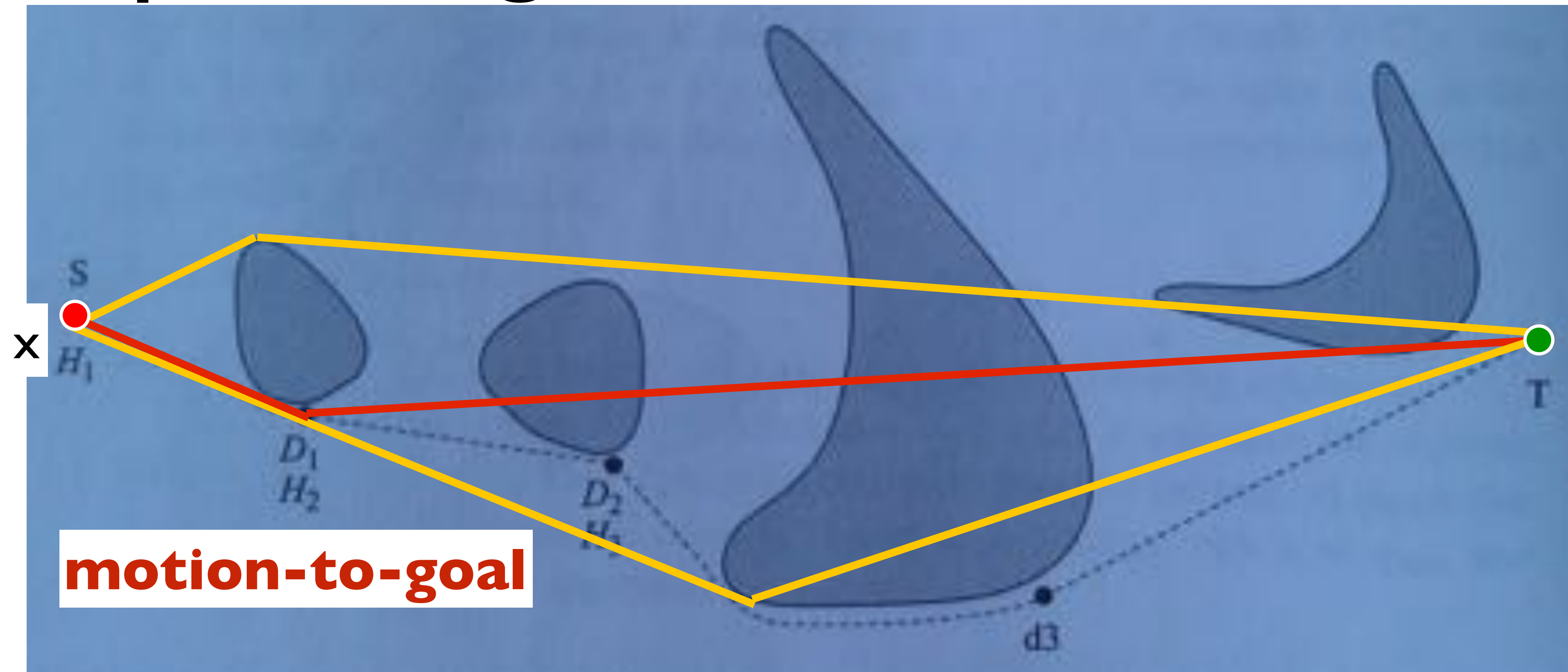
# Example: range $R=\infty$



Note:  $T$  is known when  $R=\infty$

$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima

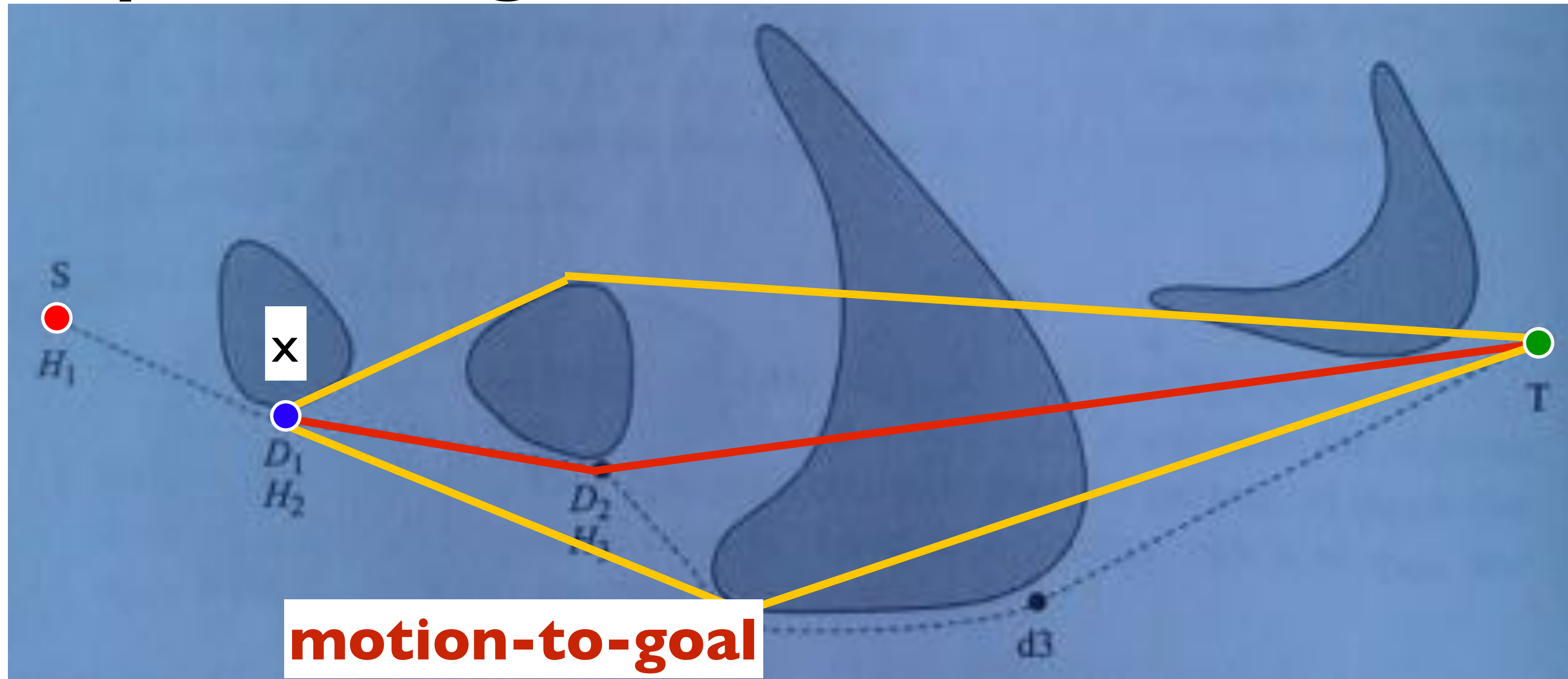
# Example: range $R=\infty$



min  $G(x)$  in red, others in yellow

$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima

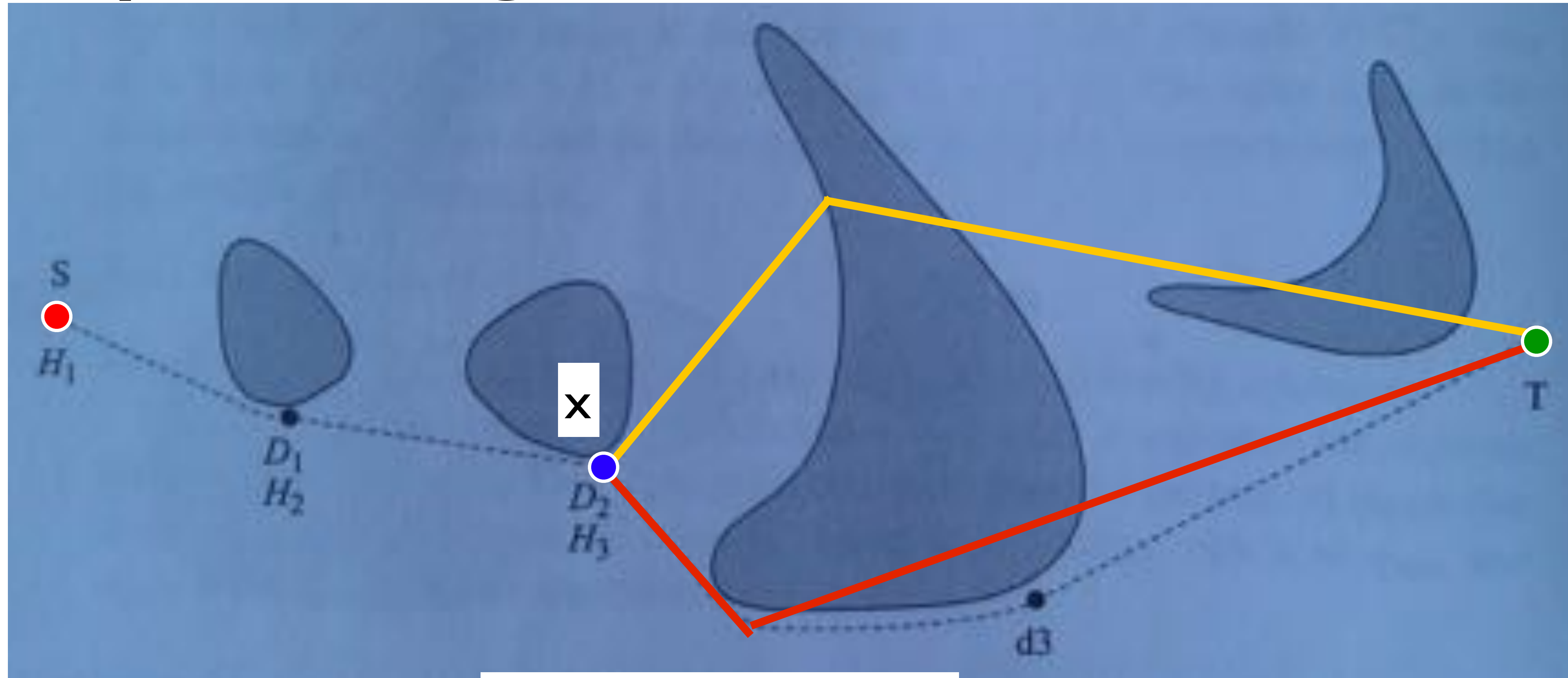
# Example: range $R=\infty$



$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima



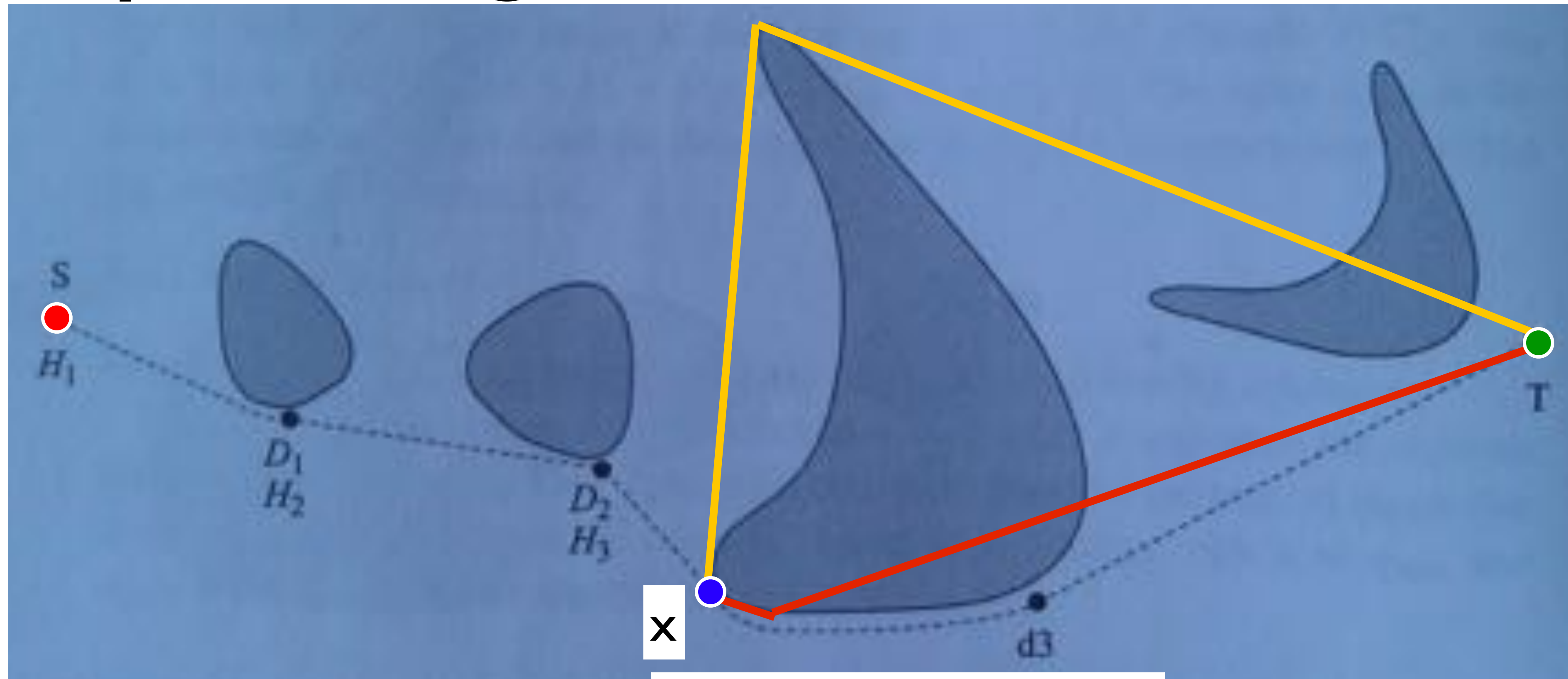
# Example: range $R=\infty$



**motion-to-goal**

$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima

# Example: range $R=\infty$



**follow-boundary**

start following:

$$\min d(q_{goal}, \{\text{visible } O_i\}) < \min d(q_{goal}, \text{sensed}(WO_j))$$

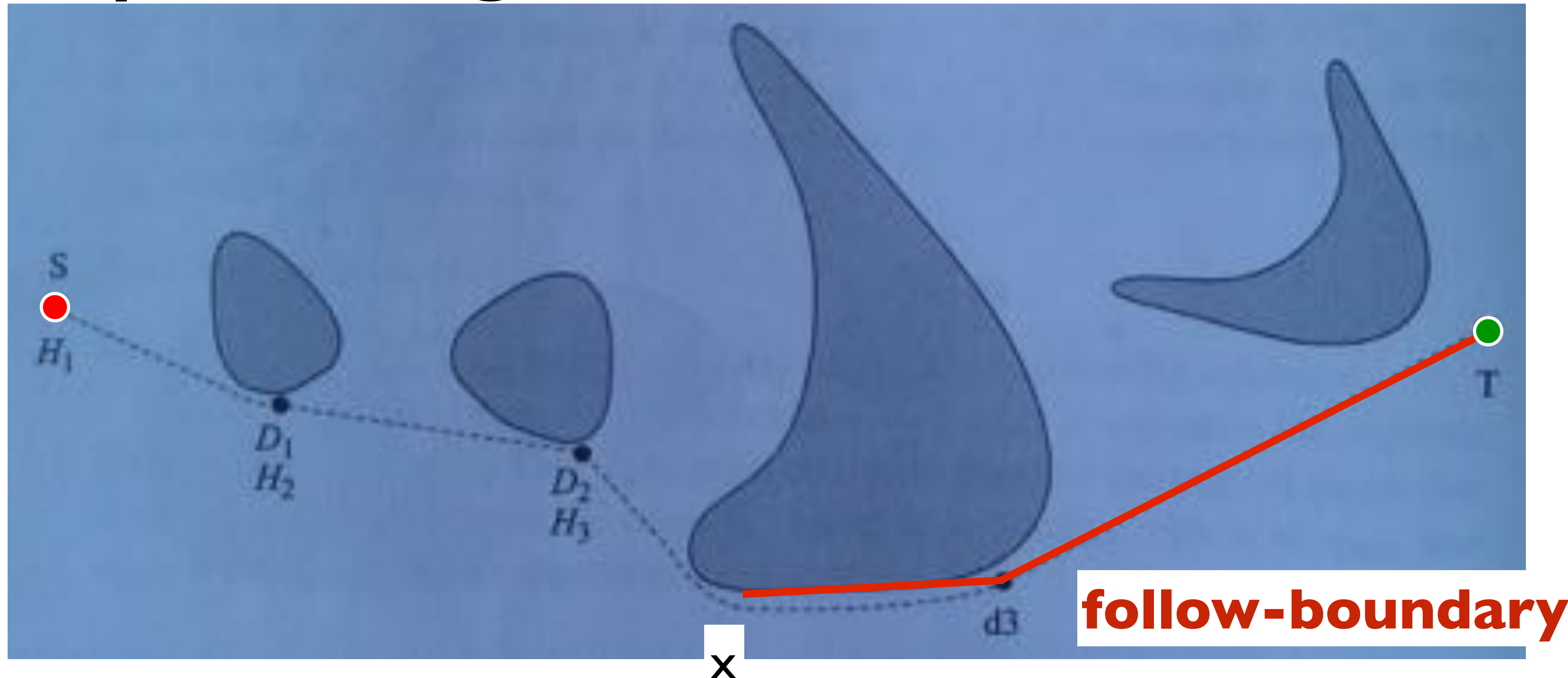
$H_i$ : hit point

$D_i$ : Depart point

$L_i$ : Leave point

$M_i$ : local minima

# Example: range $R=\infty$



end following:

$$\min d(q_{goal}, \{\text{visible } O_i\}) < \min d(q_{goal}, \text{sensed}(WO_j))$$

$H_i$ : hit point

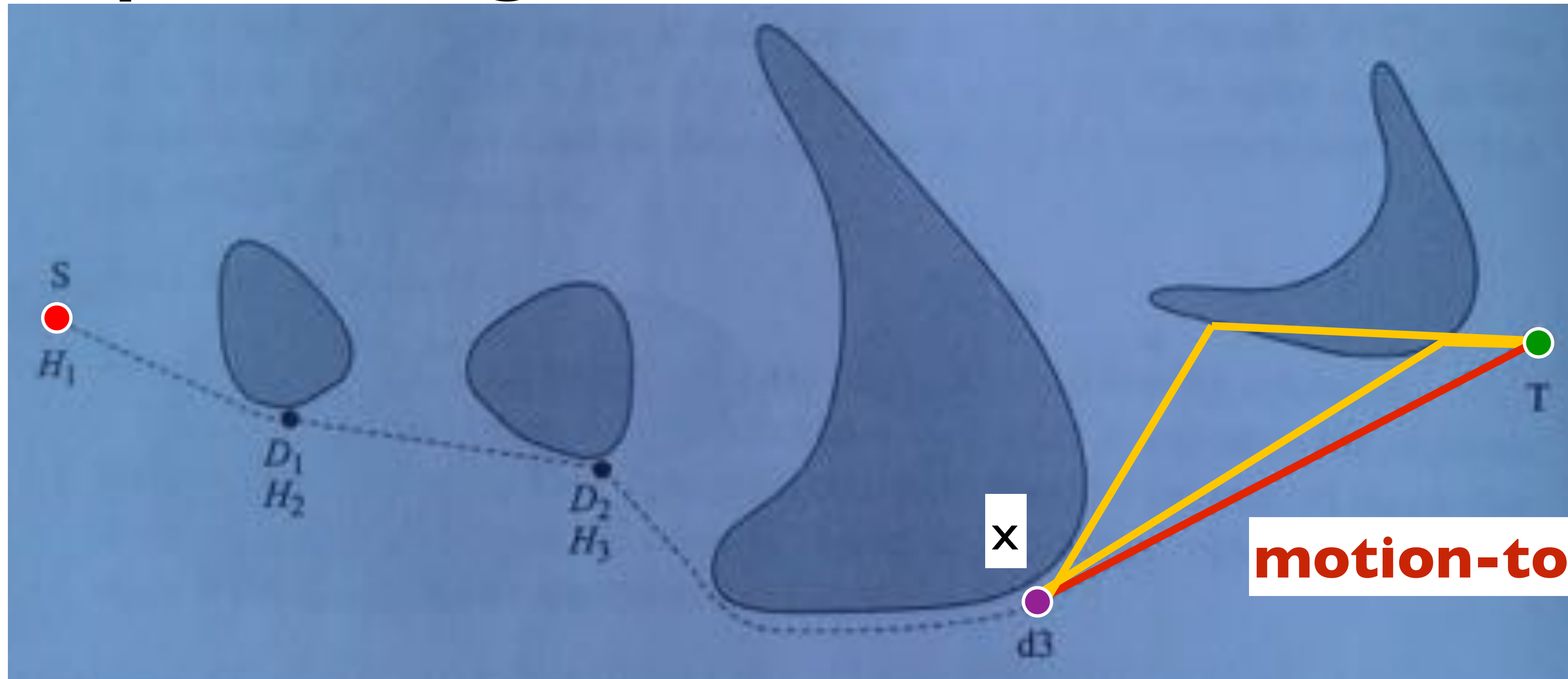
$D_i$ : Depart point

$L_i$ : Leave point

$M_i$ : local minima



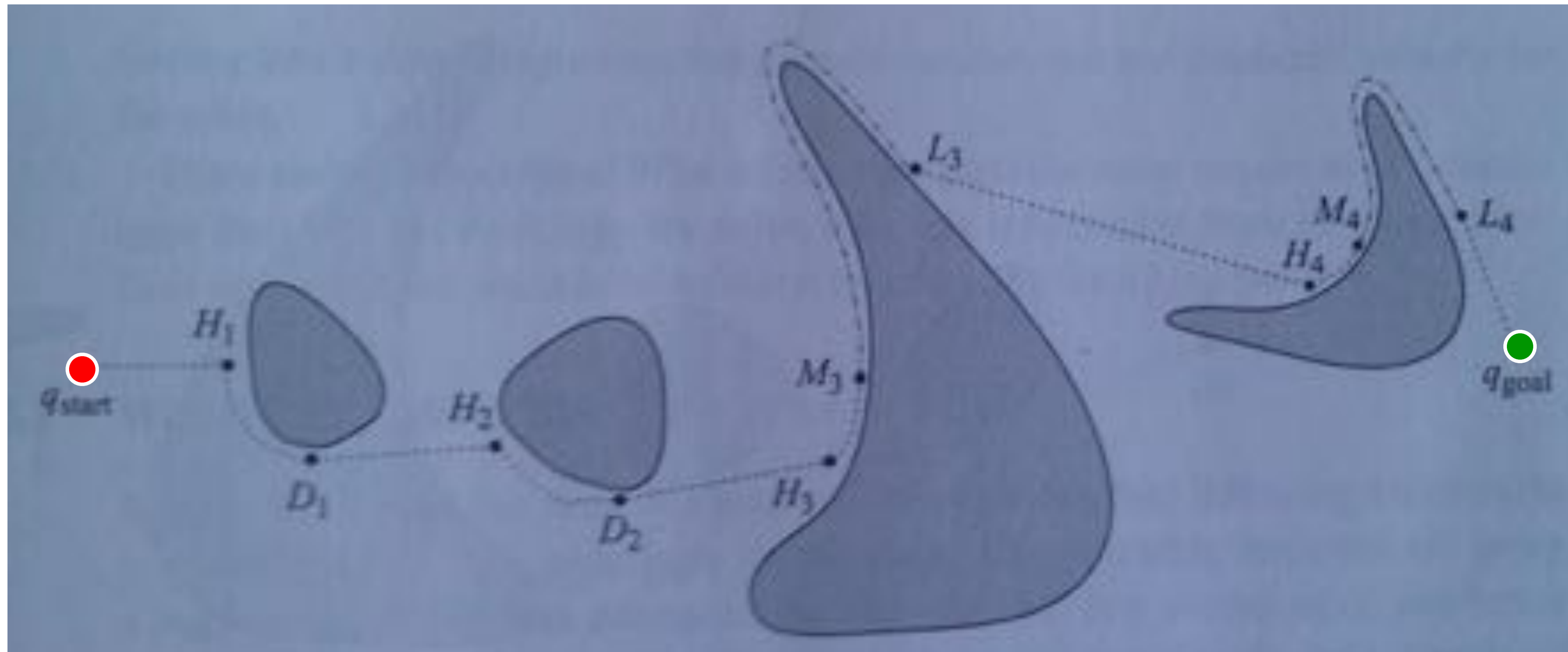
# Example: range $R=\infty$



$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima

# Example: range $R=0$

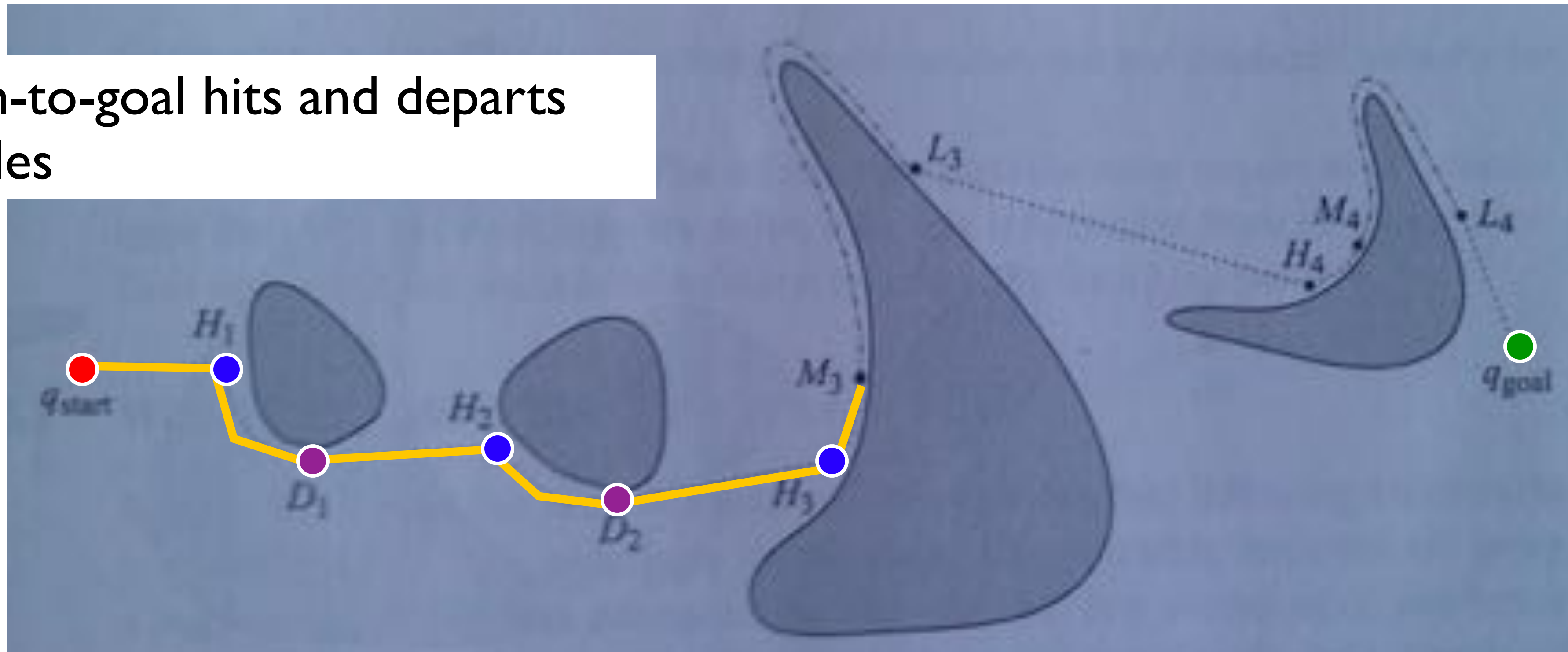
$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima



# Example: range $R=0$

$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima

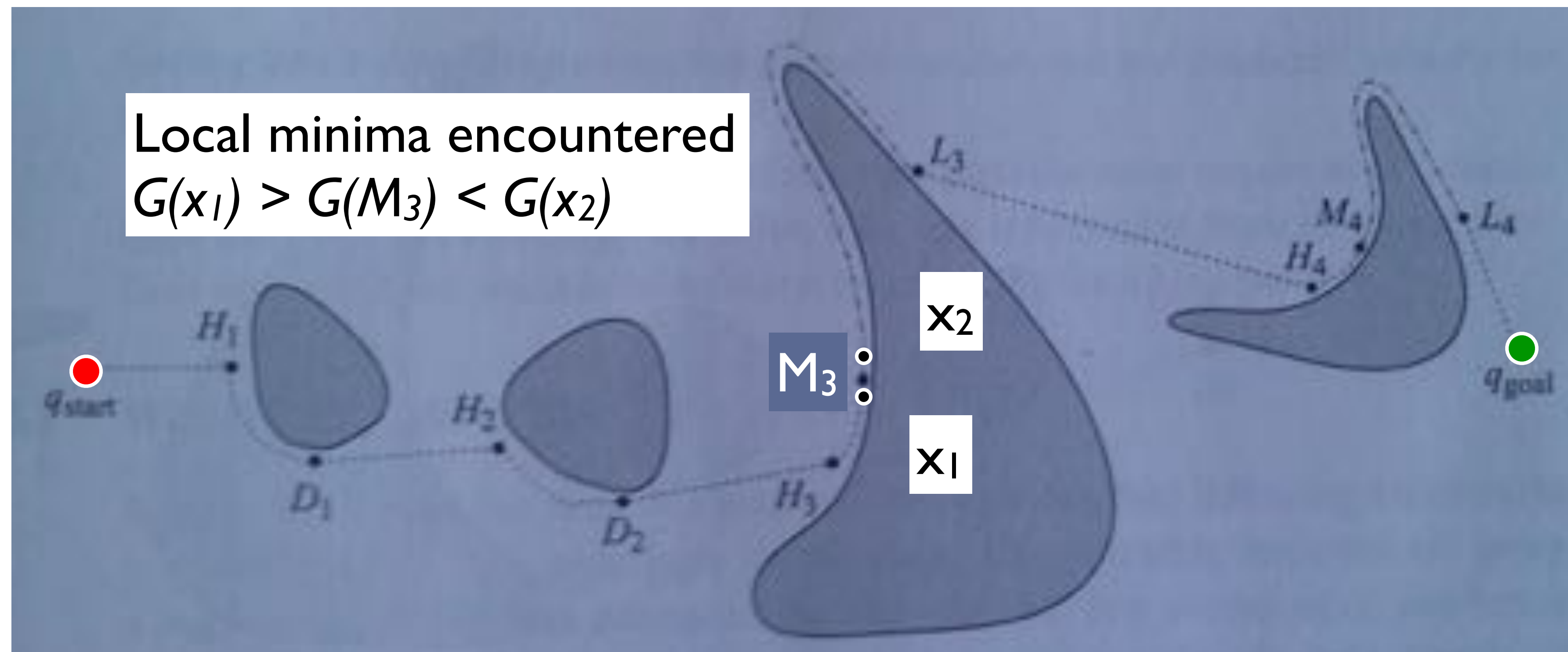
Motion-to-goal hits and departs  
obstacles





# Example: range $R=0$

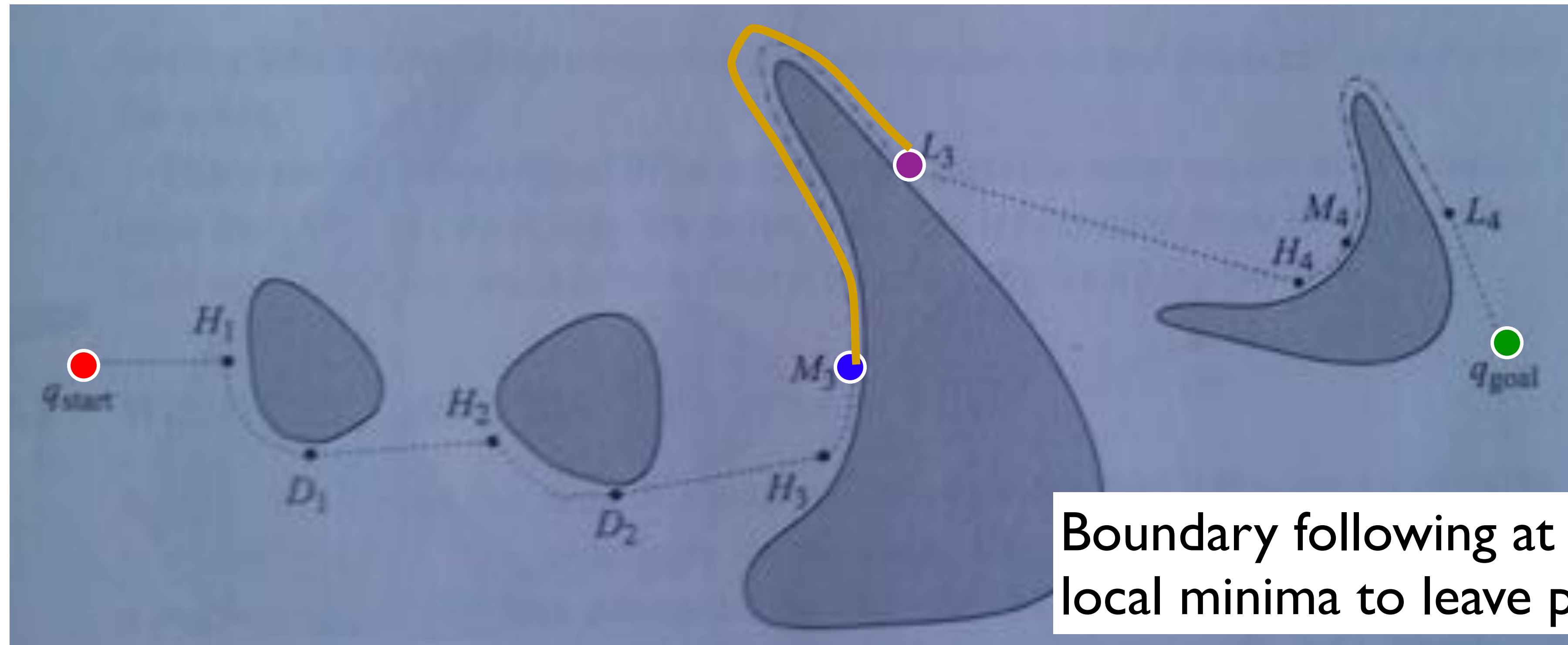
$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima



Local minima at increase of  $G(x) = d(x, O_i) + d(O_i, q_{goal})$

# Example: range $R=0$

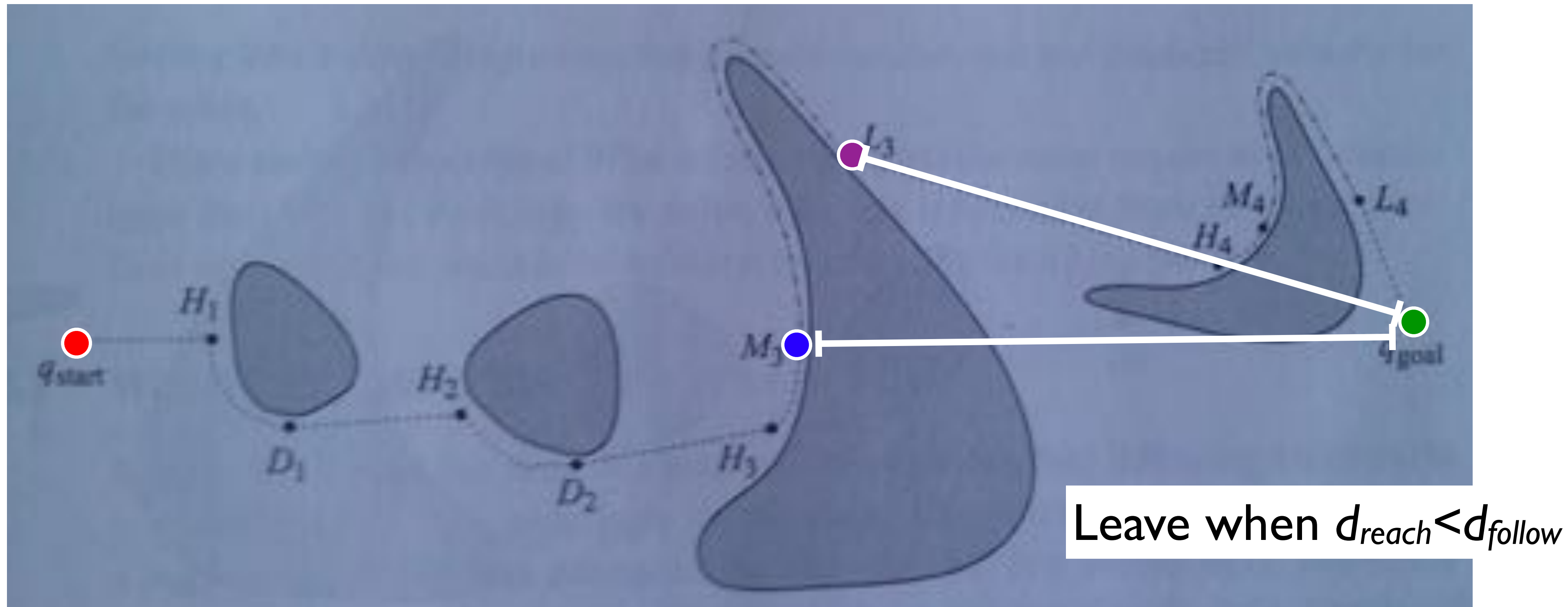
$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima



Local minima at increase of  $G(x) = d(x, O_i) + d(O_i, q_{goal})$

# Example: range $R=0$

$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima

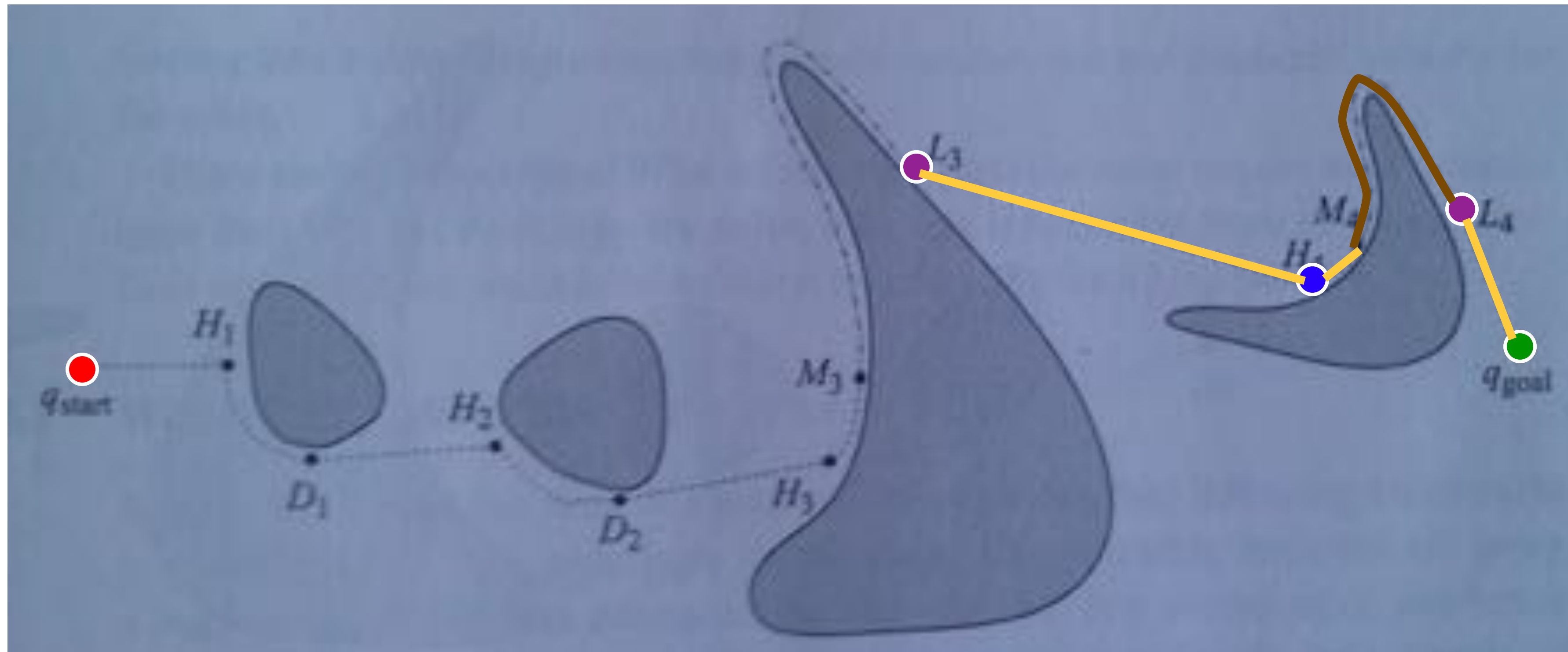


# Local minima at increase of $G(x) = d(x, O_i) + d(O_i, q_{goal})$

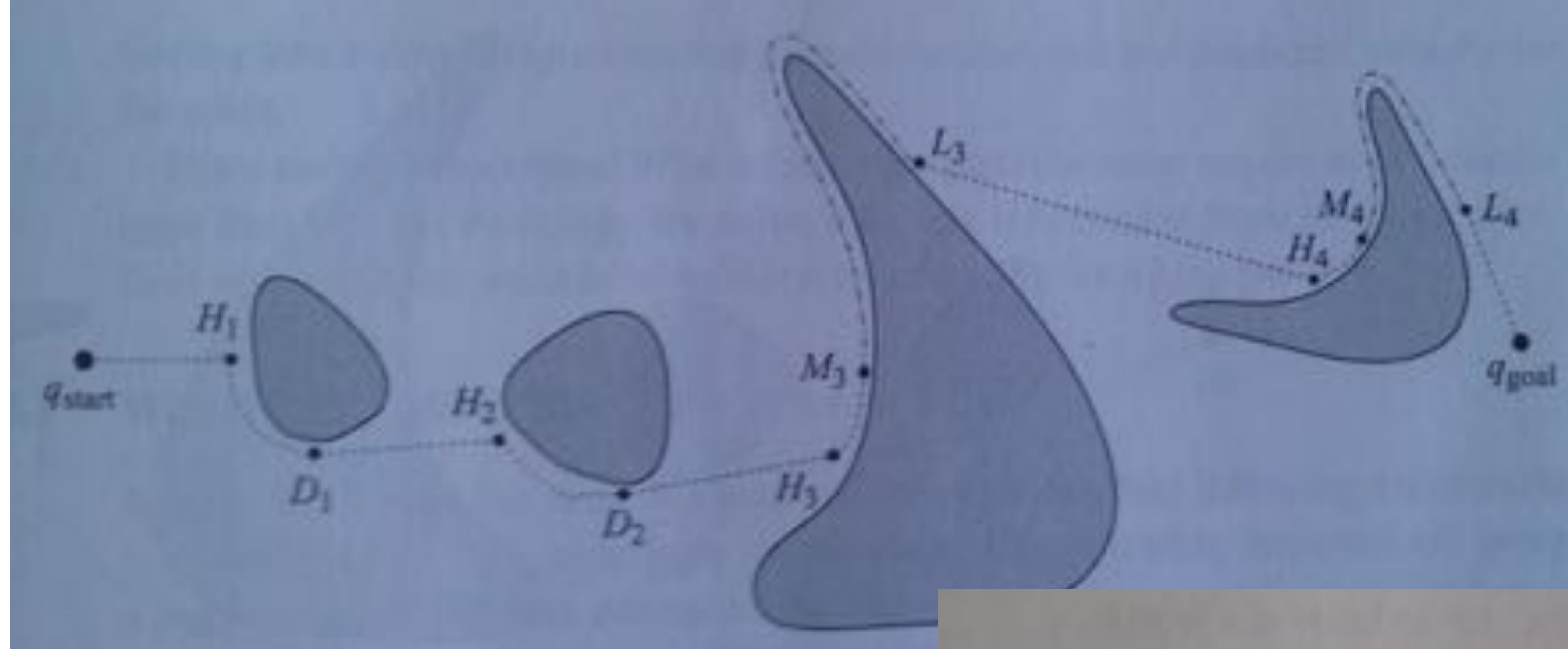


# Example: range $R=0$

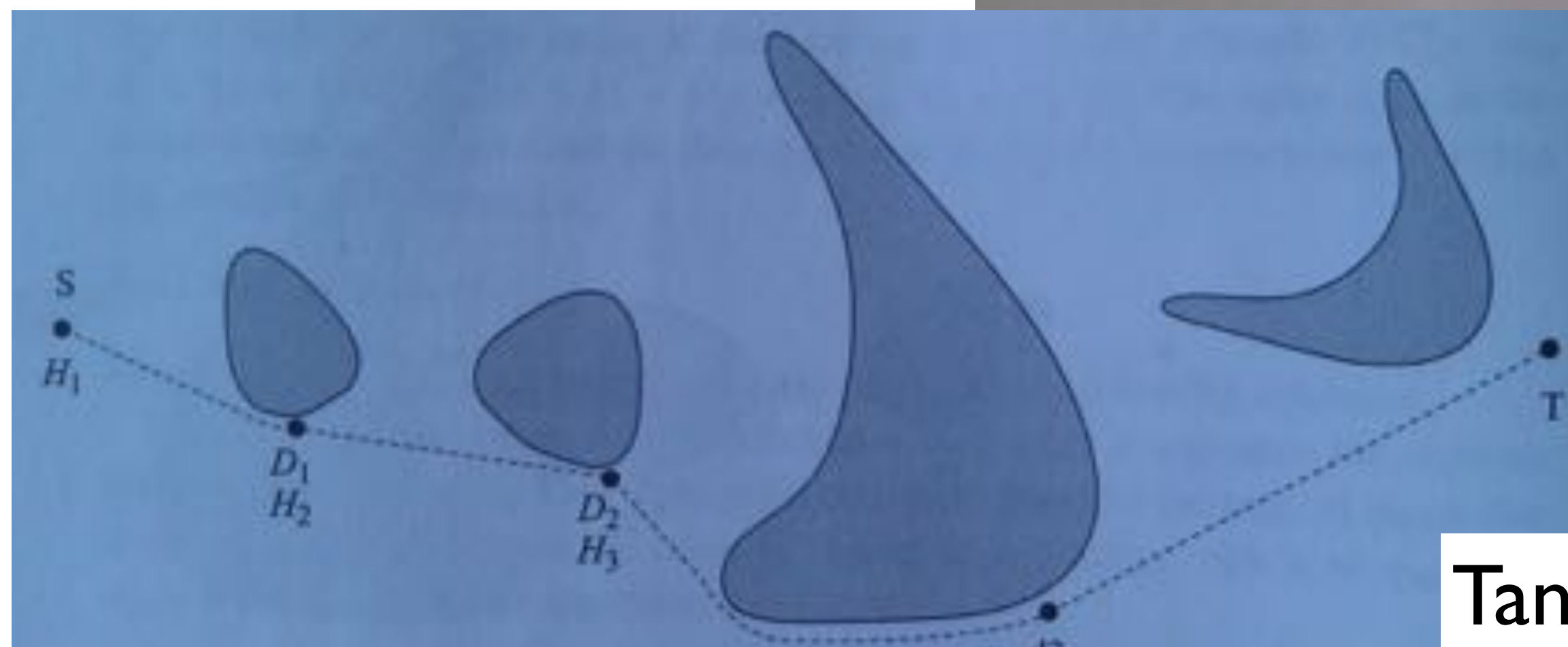
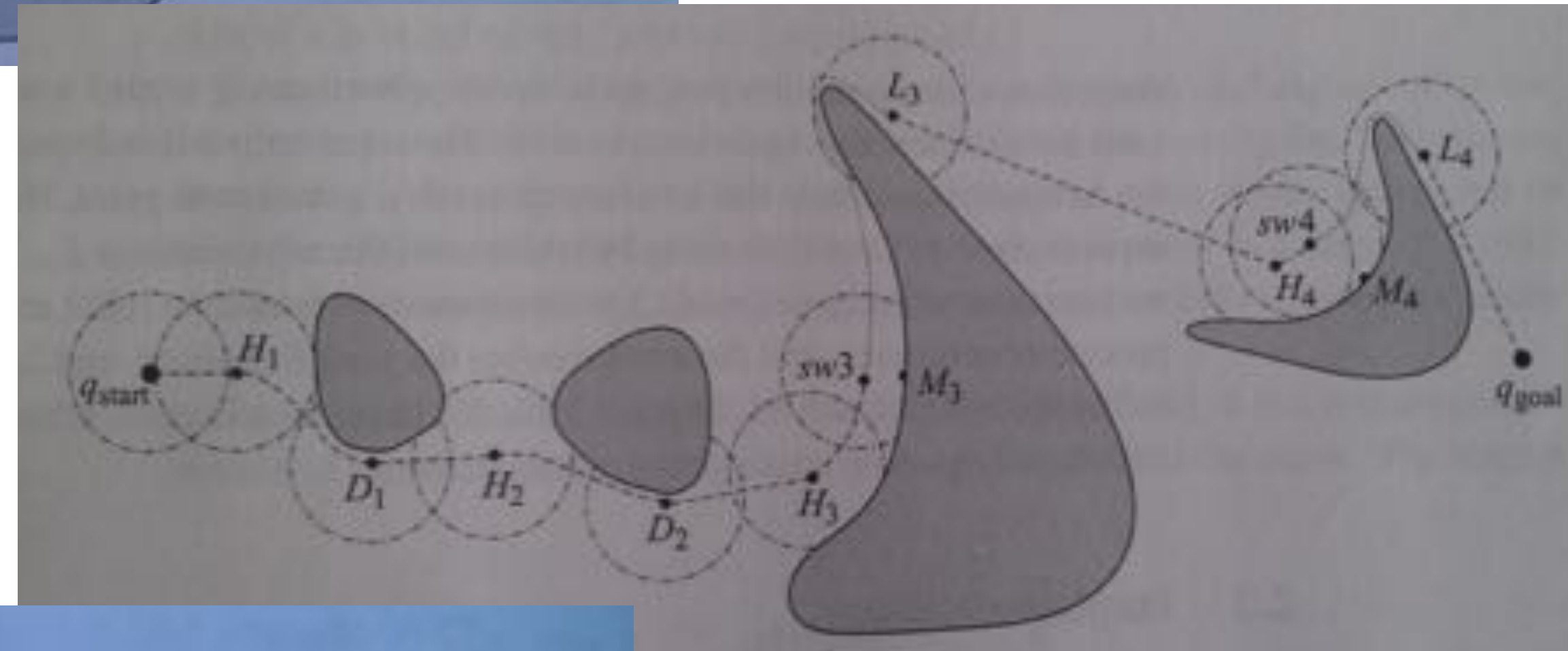
$H_i$ : hit point  
 $D_i$ : Depart point  
 $L_i$ : Leave point  
 $M_i$ : local minima



Tangent bug  $R=0$



Tangent bug with limited radius



Tangent bug  $R=\infty$

What does BugX assume that Random Walk does not?





What does BugX assume that Random Walk does not?

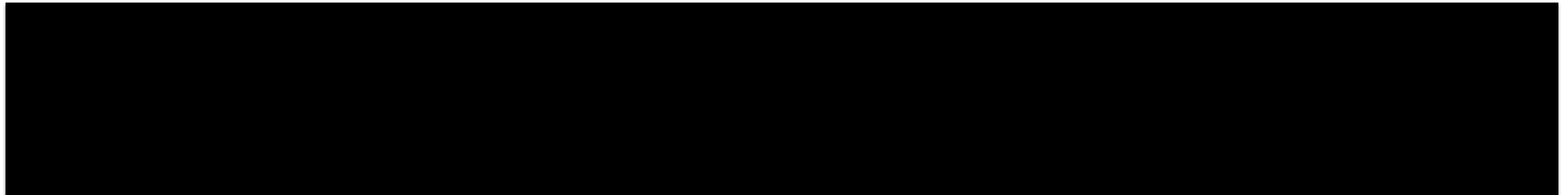
Localization: knowing the robot's location, at least wrt. distance to goal



What does BugX assume that Random Walk does not?

Localization: knowing the robot's location, at least wrt. distance to goal

What do graph search algorithms assume that BugX does not?



What does BugX assume that Random Walk does not?

Localization: knowing the robot's location, at least wrt. distance to goal

What do graph search algorithms assume that BugX does not?

A graph of valid locations that can be traversed

Suppose we have or can build such a graph...





# Next Lecture

## Planning - III - Configuration Space

