AA 274A: Principles of Robot Autonomy I
Problem Set 2

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Problem 1

(i) See code

(ii)

A* Motion Planning

In [83]:
```
# The autoreload extension will automatically load in new code as you edit file
# so you don't need to restart the kernel every time
%load_ext autoreload
%autoreload 2
import numpy as np
import matplotlib.pyplot as plt
from P1_astar import DetOccupancyGrid2D, AStar
from utils import generate_planning_problem
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

Simple Environment

Workspace

(Try changing this and see what happens)

In [98]:
```
width = 10
height = 10
obstacles = [((6,7),(8,8)),((2,2),(4,3)),((2,5),(4,7)),((6,3),(8,5))]
occupancy = DetOccupancyGrid2D(width, height, obstacles)
```

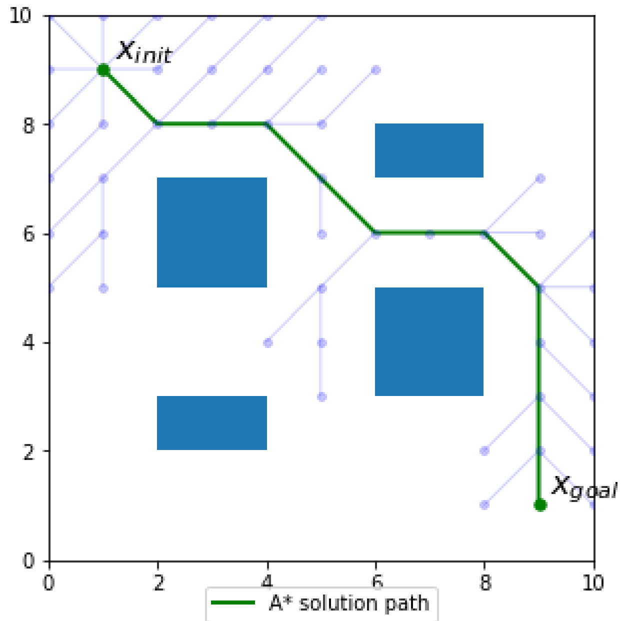
Starting and final positions

(Try changing these and see what happens)

In [99]:
```
x_init = (1, 9)
x_goal = (9, 1)
```

Run A* planning

In [100…
```
astar = AStar((0, 0), (width, height), x_init, x_goal, occupancy)
if not astar.solve():
    print("No path found")
else:
    plt.rcParams['figure.figsize'] = [5, 5]
    astar.plot_path()
    astar.plot_tree()
```



Random Cluttered Environment

Generate workspace, start and goal positions

(Try changing these and see what happens)

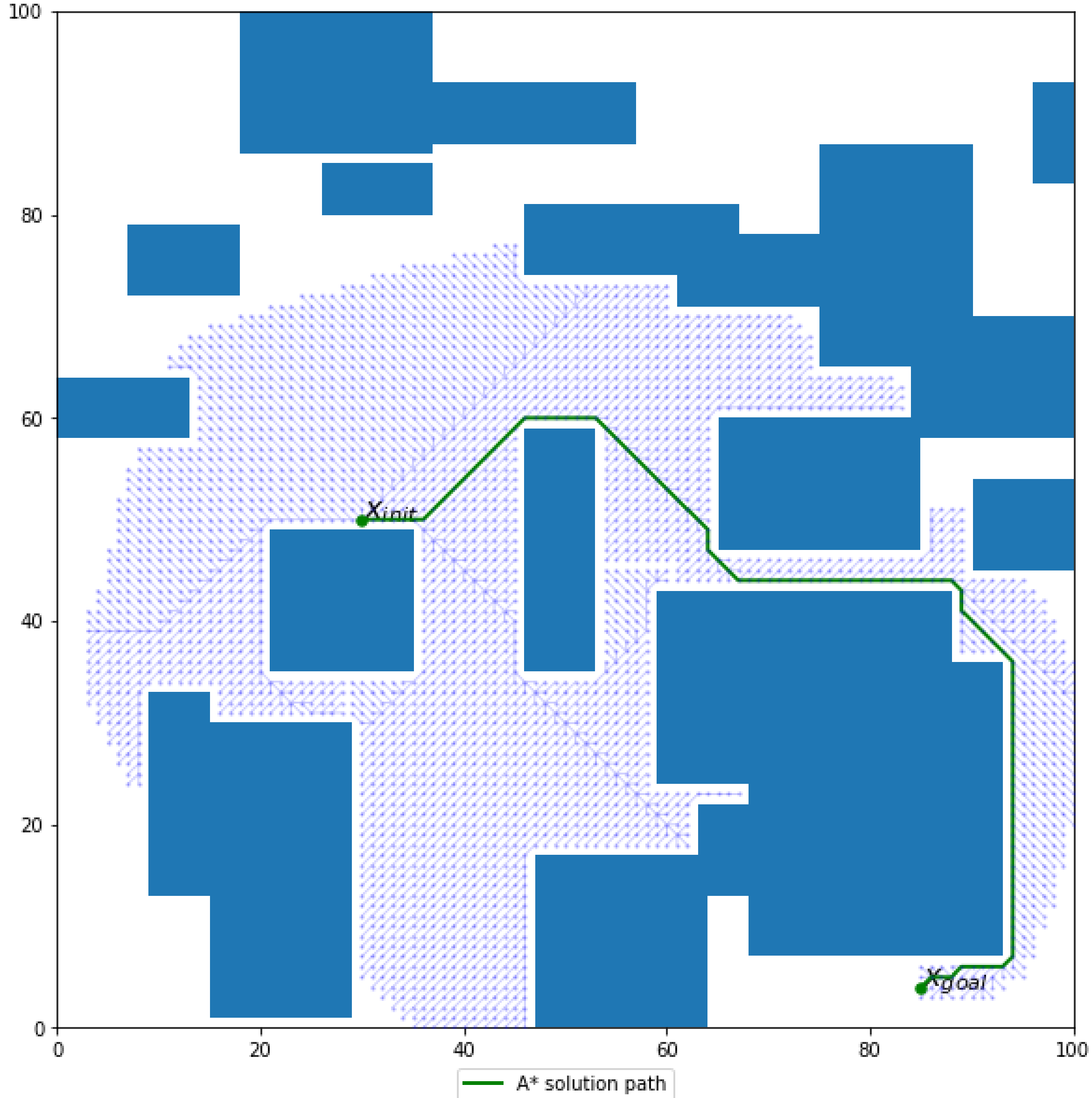
In [113…

```
width = 100
height = 100
num_obs = 25
min_size = 5
max_size = 30

occupancy, x_init, x_goal = generate_planning_problem(width, height, num_obs, m
```

Run A* planning

In [114…

```
astar = AStar((0, 0), (width, height), x_init, x_goal, occupancy)
if not astar.solve():
    print("No path found")
else:
    plt.rcParams['figure.figsize'] = [10, 10]
    astar.plot_path()
    astar.plot_tree(point_size=2)
```



In [ ]:

In [ ]:

In [ ]:

Problem 2

(i) See code

(ii) See code

(iii) See code

(iv)

RRT Sampling-Based Motion Planning

In [1]:
```
# The autoreload extension will automatically load in new code as you edit file
# so you don't need to restart the kernel every time
%load_ext autoreload
%autoreload 2

import numpy as np
import matplotlib.pyplot as plt
from P2_rrt import *

plt.rcParams['figure.figsize'] = [8, 8] # Change default figure size
```

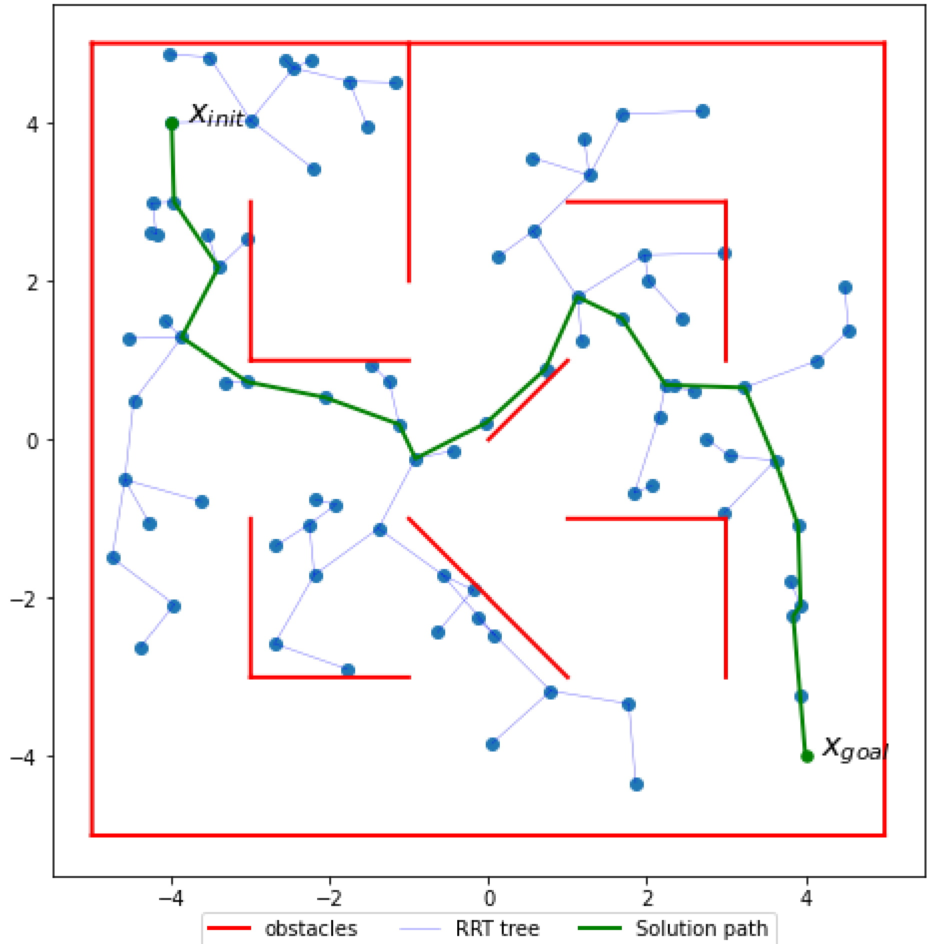
Set up workspace

In [2]:
```
MAZE = np.array([
    (( 5, 5), (-5, 5)),
    ((-5, 5), (-5,-5)),
    ((-5,-5), ( 5,-5)),
    (( 5,-5), ( 5, 5)),
    ((-3,-3), (-3,-1)),
    ((-3,-3), (-1,-3)),
    (( 3, 3), ( 3, 1)),
    (( 3, 3), ( 1, 3)),
    (( 1,-1), ( 3,-1)),
    (( 3,-1), ( 3,-3)),
    ((-1, 1), (-3, 1)),
    ((-3, 1), (-3, 3)),
    ((-1,-1), ( 1,-3)),
    ((-1, 5), (-1, 2)),
    (( 0, 0), ( 1, 1))
])

# try changing these!
x_init = [-4,4] # reset to [-4,4] when saving results for submission
x_goal = [4,-4] # reset to [4,-4] when saving results for submission
```

Geometric Planning

In [3]:
```
grrt = GeometricRRT([-5,-5], [5,5], x_init, x_goal, MAZE)
grrt.solve(1.0, 2000)
```

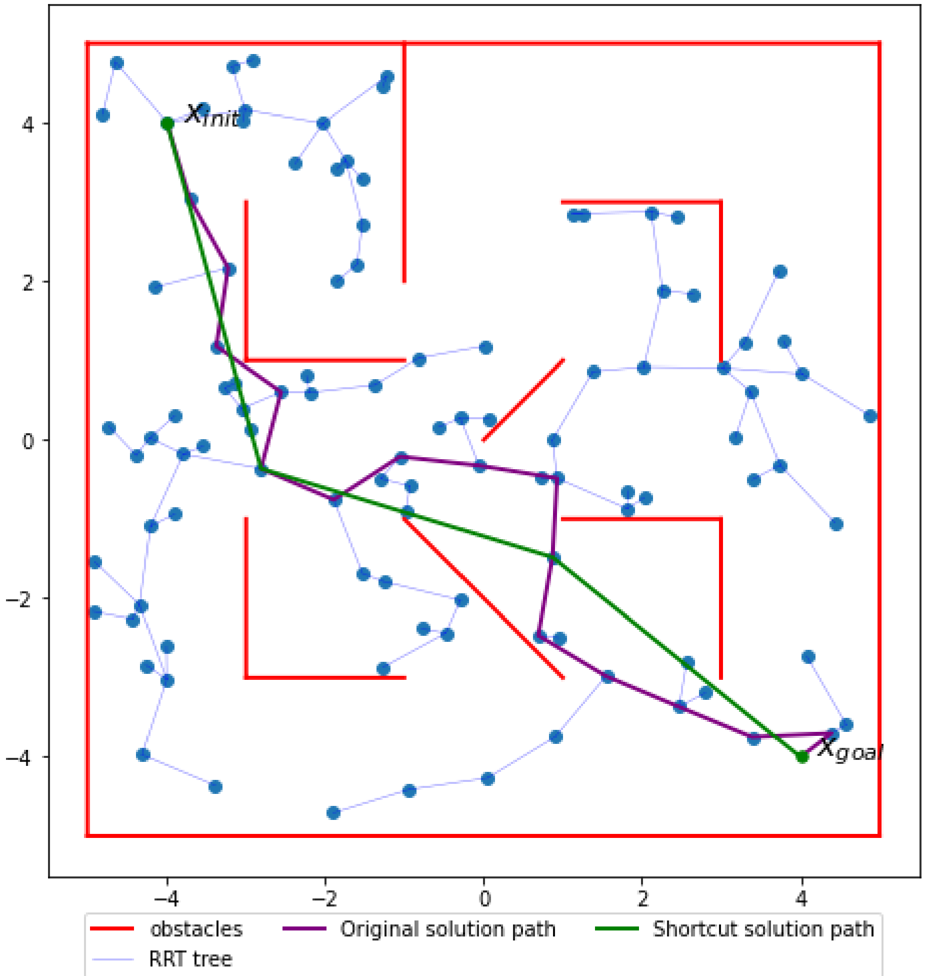
Out[3]:
```
True
```



Adding shortcutting

In [4]:
```
grrt.solve(1.0, 2000, shortcut=True)
```

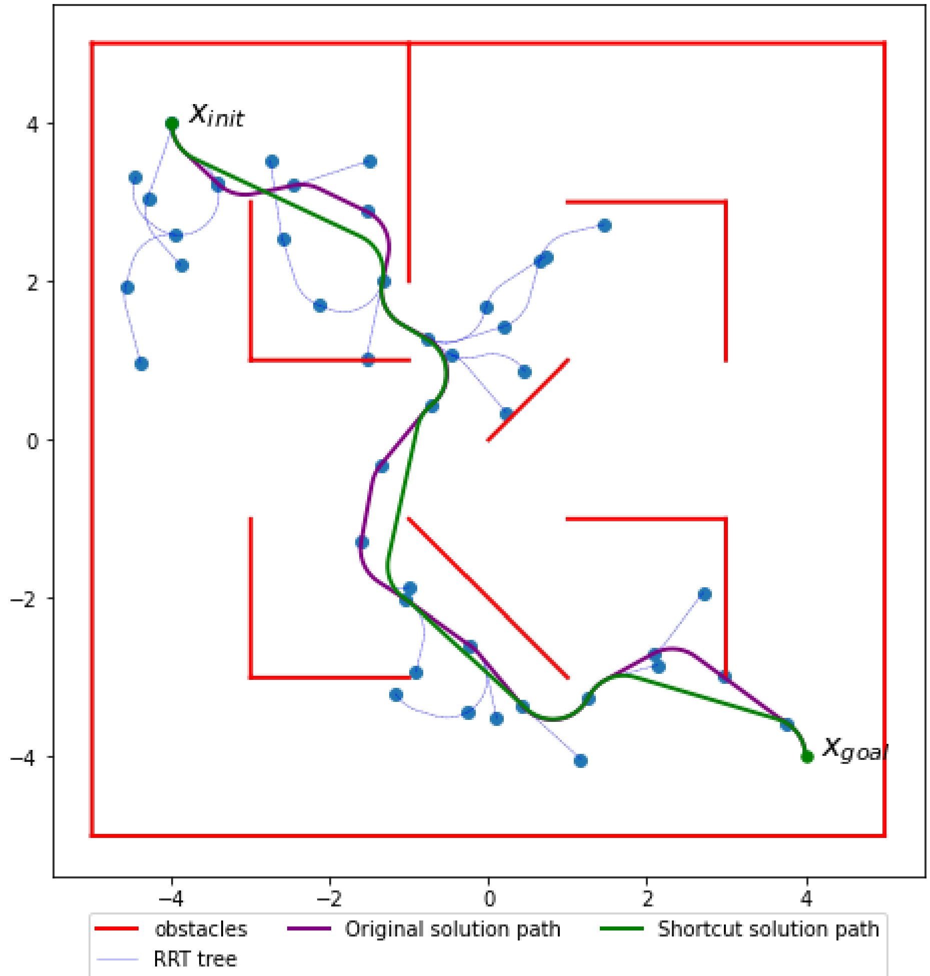
Out[4]:
```
True
```



Dubins Car Planning

In [25]:
```
x_init = [-4,4, 3*np.pi/2]
x_goal = [4,-4, 3*np.pi/2]

drrt = DubinsRRT([-5,-5,0], [5,5,2*np.pi], x_init, x_goal, MAZE, .5)
drrt.solve(1.0, 1000, shortcut=True)
```

Out[25]:
```
True
```



x_{init}
x_{goal}
4
2
0
−2
−4
−4
−2
0
2
4
obstacles
Original solution path
Shortcut solution path
RRT tree

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Problem 3

(i) See code

(ii) See code

(iii) See code

(iv)

In [24]:
```
# The autoreload extension will automatically load in new code as you edit file
# so you don't need to restart the kernel every time
%load_ext autoreload
%autoreload 2

import numpy as np
from P1_astar import AStar
from P2_rrt import *
from P3_traj_planning import compute_smoothed_traj, modify_traj_with_limits, Sw
import matplotlib.pyplot as plt
from HW1.P1_differential_flatness import *
from HW1.P2_pose_stabilization import *
from HW1.P3_trajectory_tracking import *
from utils import generate_planning_problem
from HW1.utils import simulate_car_dyn

plt.rcParams['figure.figsize'] = [14, 14] # Change default figure size
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

Generate workspace, start and goal positions

In [25]:
```
width = 100
height = 100
num_obs = 25
min_size = 5
max_size = 30

occupancy, x_init, x_goal = generate_planning_problem(width, height, num_obs, m
```

Solve A* planning problem

In [26]:
```
astar = AStar((0, 0), (width, height), x_init, x_goal, occupancy)
if not astar.solve():
    print("No path found")
```

Smooth Trajectory Generation

Trajectory parameters

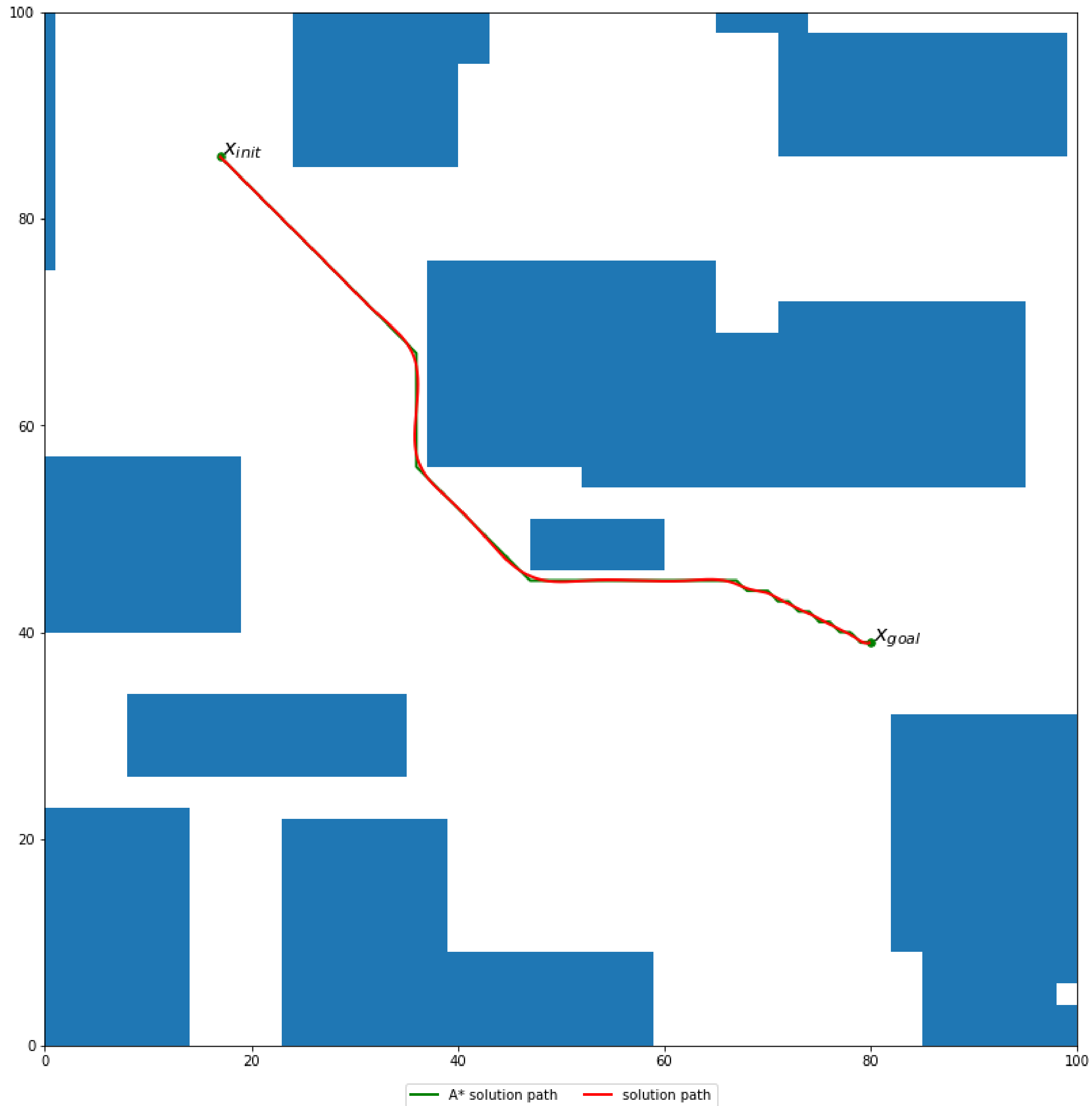
(Try changing these and see what happens)

In [27]:
```
V_des = 0.3  # Nominal velocity
alpha = 0.8   # Smoothness parameter
dt = 0.05
k_spline = 3
```

Generate smoothed trajectory

In [28]:
```
t_smoothed, traj_smoothed = compute_smoothed_traj(astar.path, V_des, k_spline,
```

```
fig = plt.figure()
astar.plot_path(fig.number)
def plot_traj_smoothed(traj_smoothed):
    plt.plot(traj_smoothed[:,0], traj_smoothed[:,1], color="red", linewidth=2,
plot_traj_smoothed(traj_smoothed)
plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.03), fancybox=True, ncol
plt.show()
```



Control-Feasible Trajectory Generation and Tracking

Robot control limits

In [29]:
```
V_max = 0.5 # max speed
om_max = 1 # max rotational speed
```

Tracking control gains

Tune these as needed to improve tracking performance.

In [30]:
```
kpx = 2
kpy = 2
kdx = 2
kdy = 2
```

Generate control-feasible trajectory

In [31]:
```
t_new, V_smooth_scaled, om_smooth_scaled, traj_smooth_scaled = modify_traj_with
```

Create trajectory controller and load trajectory

In [32]:
```
traj_controller = TrajectoryTracker(kpx=kpx, kpy=kpy, kdx=kdx, kdy=kdy, V_max=V
traj_controller.load_traj(t_new, traj_smooth_scaled)
```

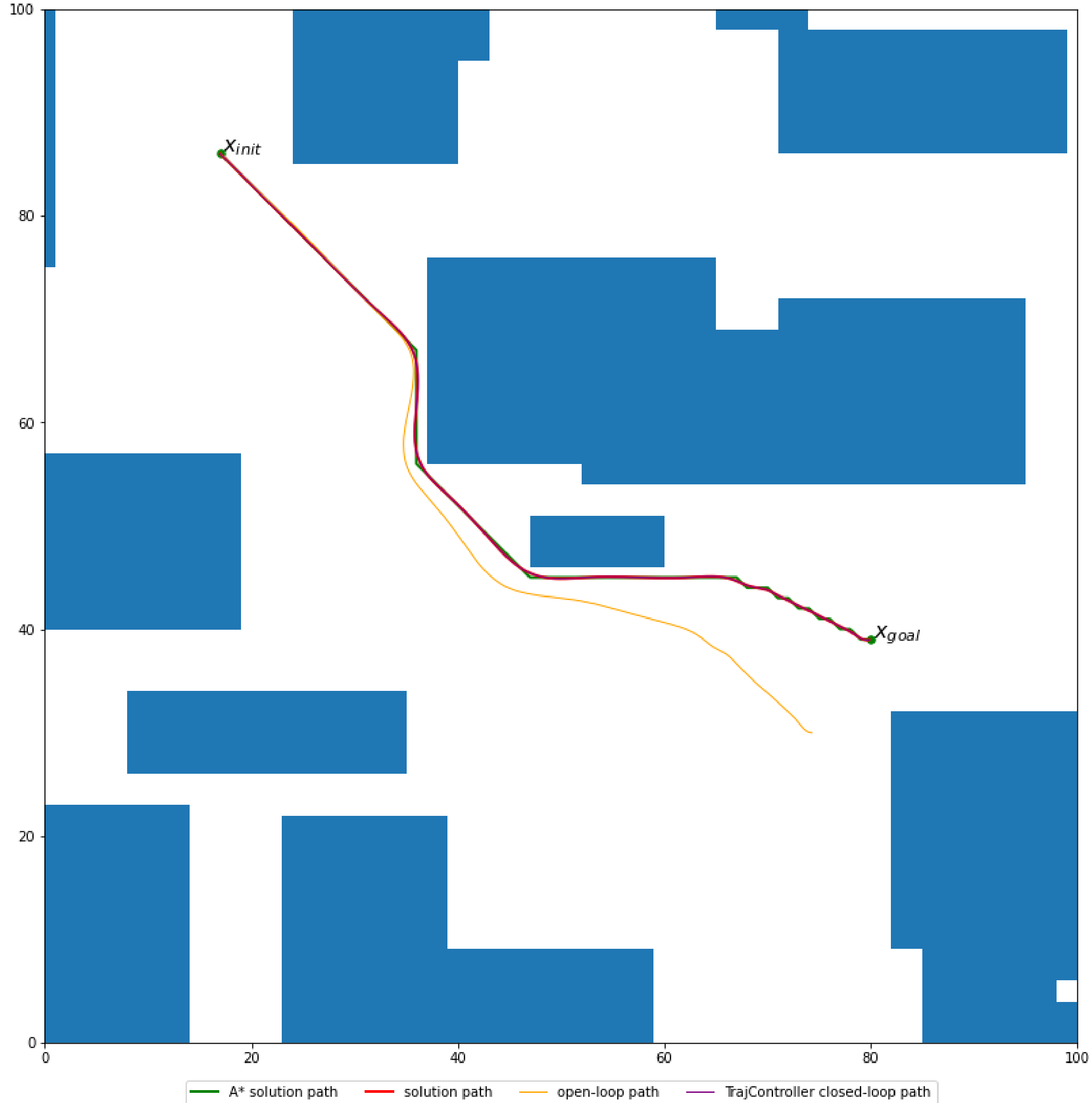
Set simulation input noise

(Try changing this and see what happens)

In [33]:
```
noise_scale = 0.05
```

Simulate closed-loop tracking of smoothed trajectory, compare to open-loop

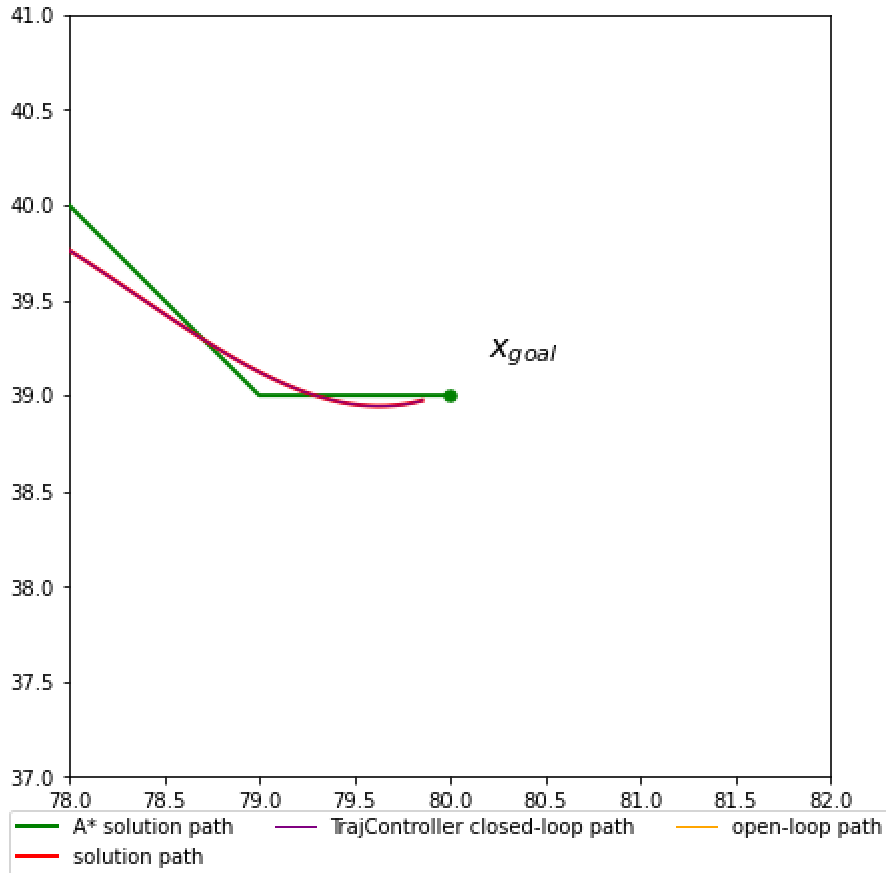
In [34]:
```
tf_actual = t_new[-1]
times_cl = np.arange(0, tf_actual, dt)
s_0 = State(x=x_init[0], y=x_init[1], V=V_max, th=traj_smooth_scaled[0,2])
s_f = State(x=x_goal[0], y=x_goal[1], V=V_max, th=traj_smooth_scaled[-1,2])

actions_ol = np.stack([V_smooth_scaled, om_smooth_scaled], axis=-1)
states_ol, ctrl_ol = simulate_car_dyn(s_0.x, s_0.y, s_0.th, times_cl, actions=a
states_cl, ctrl_cl = simulate_car_dyn(s_0.x, s_0.y, s_0.th, times_cl, controlle

fig = plt.figure()
astar.plot_path(fig.number)
plot_traj_smoothed(traj_smoothed)
def plot_traj_ol(states_ol):
    plt.plot(states_ol[:,0],states_ol[:,1], color="orange", linewidth=1, label=
def plot_traj_cl(states_cl):
    plt.plot(states_cl[:,0], states_cl[:,1], color="purple", linewidth=1, label
plot_traj_ol(states_ol)
plot_traj_cl(states_cl)
plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.03), fancybox=True, ncol
plt.show()
```



Switching from Trajectory Tracking to Pose Stabilization Control

Zoom in on final pose error

In [35]:
```
l_window = 4.

fig = plt.figure(figsize=[7,7])
astar.plot_path(fig.number, show_init_label = False)
plot_traj_smoothed(traj_smoothed)
plot_traj_cl(states_cl)
plot_traj_ol(states_ol)
plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.03), fancybox=True, ncol
plt.axis([x_goal[0]-l_window/2, x_goal[0]+l_window/2, x_goal[1]-l_window/2, x_g
plt.show()
```



Pose stabilization control gains

Tune these as needed to improve final pose stabilization.

In [36]:
```
k1 = 1.
k2 = 0.5
k3 = 0.5
```

Create pose controller and load goal pose

Note we use the last value of the smoothed trajectory as the goal heading θ

In [37]:
```
pose_controller = PoseController(k1, k2, k3, V_max, om_max)
pose_controller.load_goal(x_goal[0], x_goal[1], traj_smooth_scaled[-1,2])
```

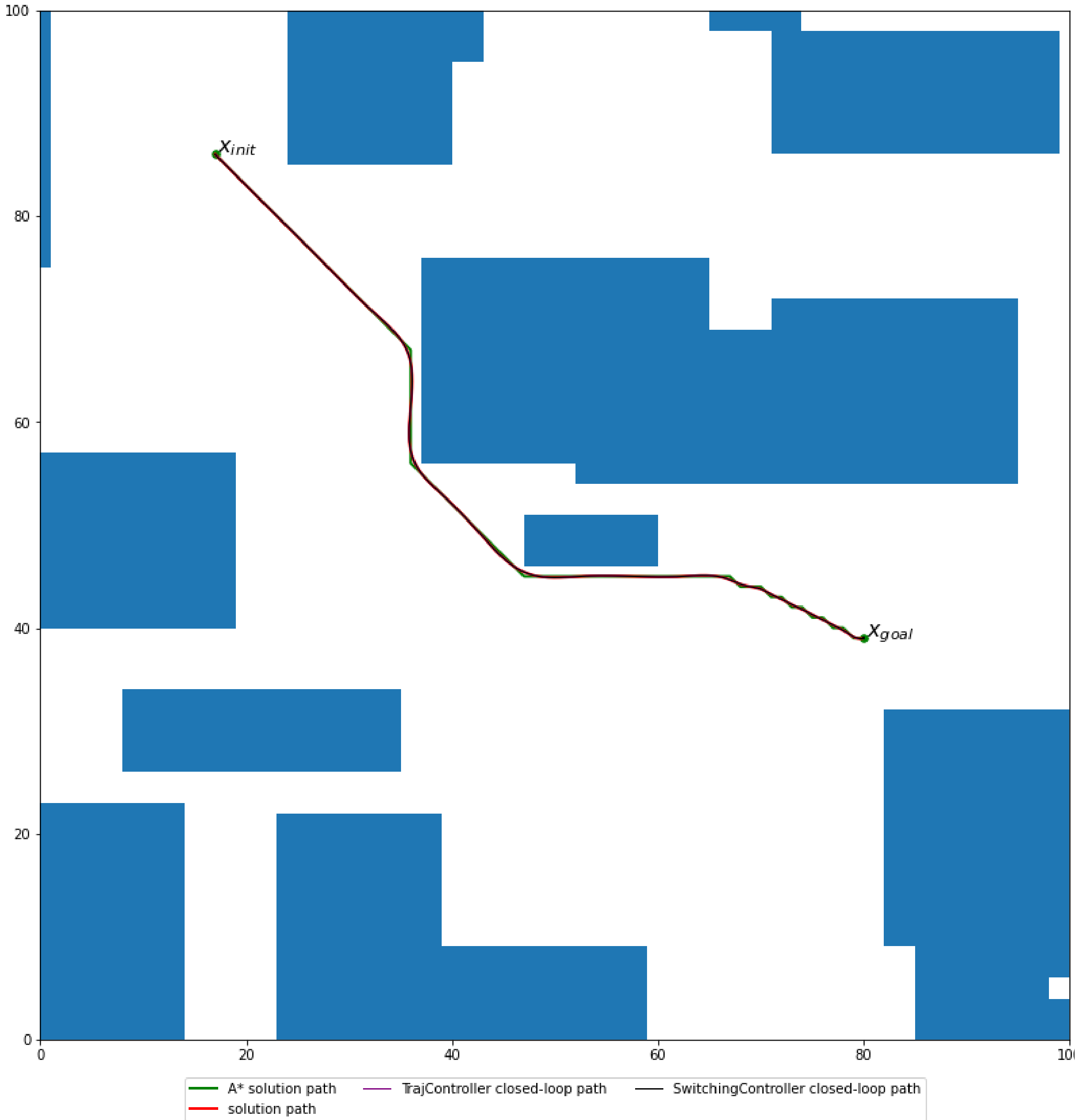
Time before trajectory-tracking completion to switch to pose stabilization

Try changing this!

In [38]:
```
t_before_switch = 5.0
```

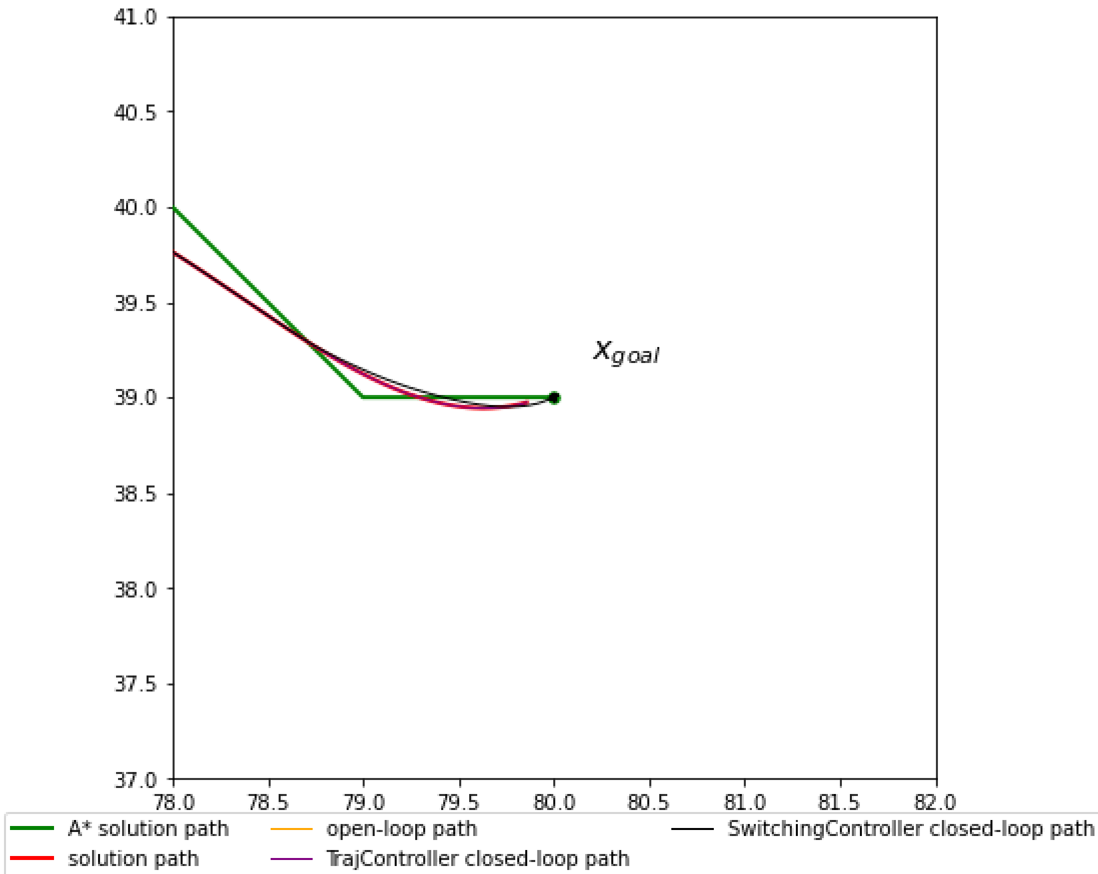
Create switching controller and compare performance

In [39]:
```
switching_controller = SwitchingController(traj_controller, pose_controller, t_

t_extend = 60.0 # Extra time to simulate after the end of the nominal trajector
times_cl_extended = np.arange(0, tf_actual+t_extend, dt)
states_cl_sw, ctrl_cl_sw = simulate_car_dyn(s_0.x, s_0.y, s_0.th, times_cl_exte

fig = plt.figure()
astar.plot_path(fig.number)
plot_traj_smoothed(traj_smoothed)
plot_traj_cl(states_cl)
def plot_traj_cl_sw(states_cl_sw):
    plt.plot(states_cl_sw[:,0], states_cl_sw[:,1], color="black", linewidth=1,
plot_traj_cl_sw(states_cl_sw)
plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.03), fancybox=True, ncol
plt.show()
```



Zoom in on final pose

In [40]:
```
l_window = 4.

fig = plt.figure(figsize=[7,7])
astar.plot_path(fig.number, show_init_label = False)
plot_traj_smoothed(traj_smoothed)
plot_traj_ol(states_ol)
plot_traj_cl(states_cl)
plot_traj_cl_sw(states_cl_sw)
plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.03), fancybox=True, ncol
plt.axis([x_goal[0]-l_window/2, x_goal[0]+l_window/2, x_goal[1]-l_window/2, x_g
plt.show()
```



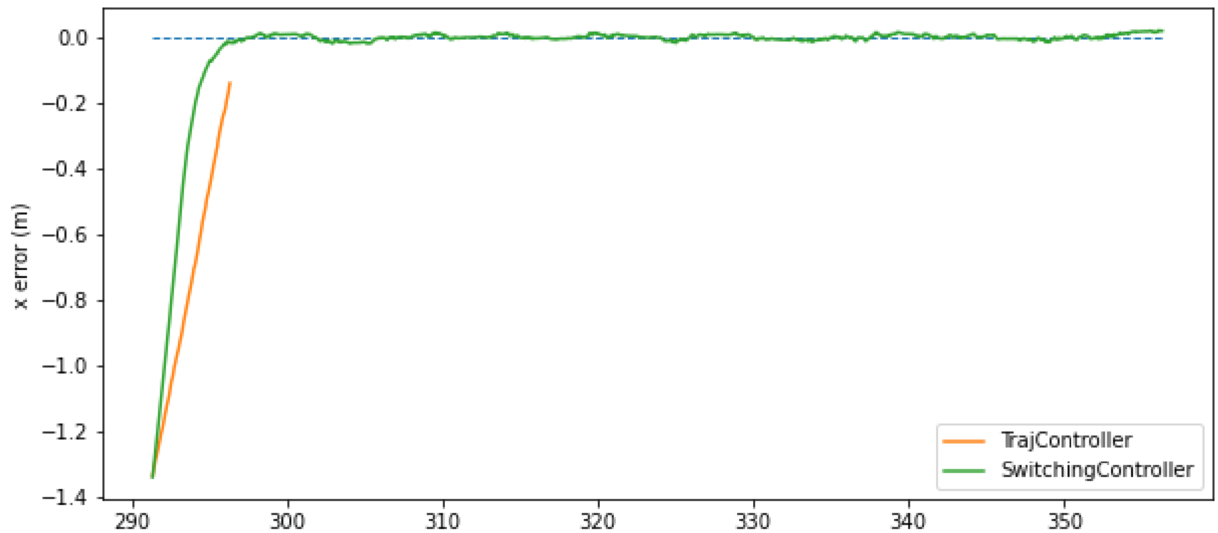
Plot final sequence of states

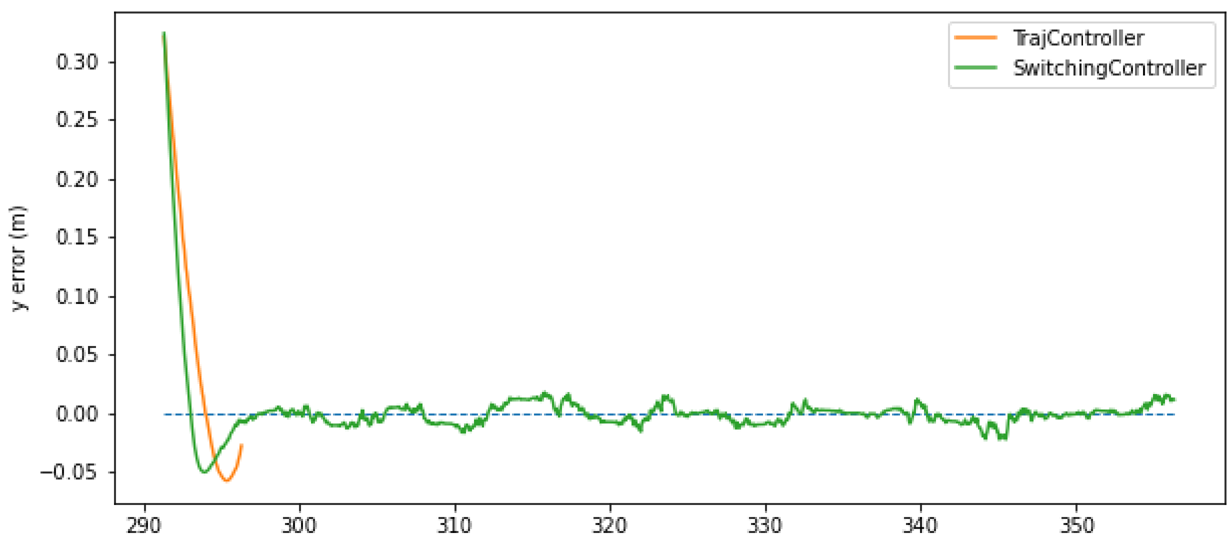
To see just how well we're able to arrive at the target point (and to assist in choosing values for the pose stabilization controller gains k_1, k_2, k_3), we plot the error in x and y for both the tracking controller and the switching controller at the end of the trajectory.

In [41]:
```
T = len(times_cl) - int(t_before_switch/dt)
fig = plt.figure(figsize=[10,10])
plt.subplot(2,1,1)
plt.plot([times_cl_extended[T], times_cl_extended[-1]], [0,0], linestyle='--',
plt.plot(times_cl[T:], states_cl[T:,0] - x_goal[0], label='TrajController')
plt.plot(times_cl_extended[T:], states_cl_sw[T:,0] - x_goal[0], label='Switchir
plt.legend()
plt.ylabel("x error (m)")
plt.subplot(2,1,2)
plt.plot([times_cl_extended[T], times_cl_extended[-1]], [0,0], linestyle='--',
plt.plot(times_cl[T:], states_cl[T:,1] - x_goal[1], label='TrajController')
```

```
plt.plot(times_cl_extended[T:], states_cl_sw[T:,1] - x_goal[1], label='Switchir
plt.legend()
plt.ylabel("y error (m)")
```

Out[41]: Text(0, 0.5, 'y error (m)')





In [ ]:

In [ ]:

In [ ]:

Problem 4

(i) See code

(ii)

```
!pip3 install reeds-shepp
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
Collecting reeds-shepp
  Downloading reeds_shepp-1.0.7.tar.gz (45 kB)
     |████████████████████████████████| 45 kB 4.0 MB/s
Building wheels for collected packages: reeds-shepp
  Building wheel for reeds-shepp (setup.py) ... done
  Created wheel for reeds-shepp: filename=reeds_shepp-1.0.7-cp37-cp37m-linux_x86_
  Stored in directory: /root/.cache/pip/wheels/db/8f/b0/cc244db2ac9927783f636ecb
Successfully built reeds-shepp
Installing collected packages: reeds-shepp
Successfully installed reeds-shepp-1.0.7
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call dr
```

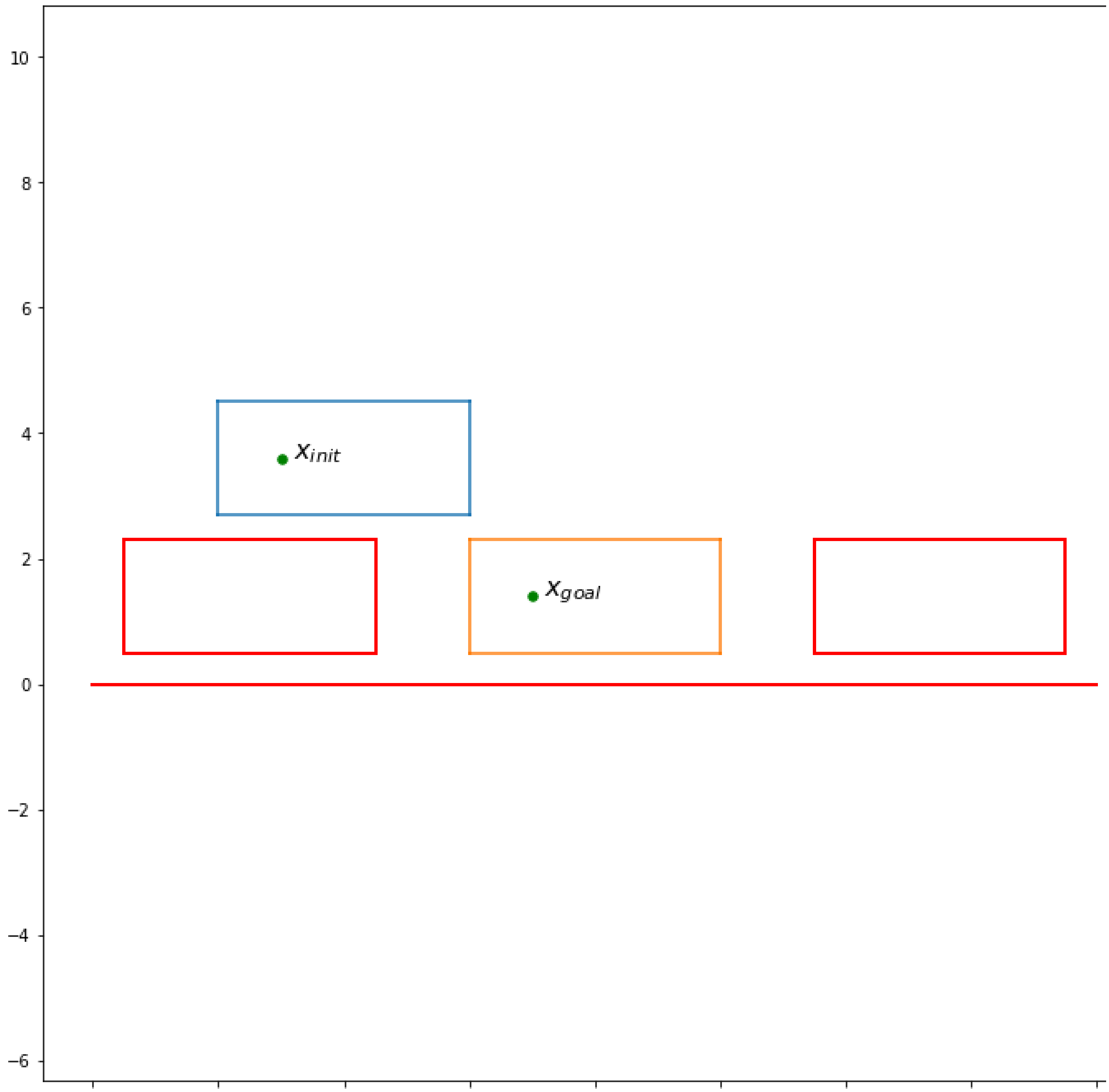
```
%cd /content/drive/My\ Drive/AA274A_HW2-master
```

```
/content/drive/My Drive/AA274A_HW2-master
```

```
# The autoreload extension will automatically load in new code as you edit files,
# so you don't need to restart the kernel every time
%load_ext autoreload
%autoreload 2

import numpy as np
import matplotlib.pyplot as plt
from P4_parallel_parking import ParkingRRT

plt.rcParams['figure.figsize'] = [12, 12]  # Change default figure size
```

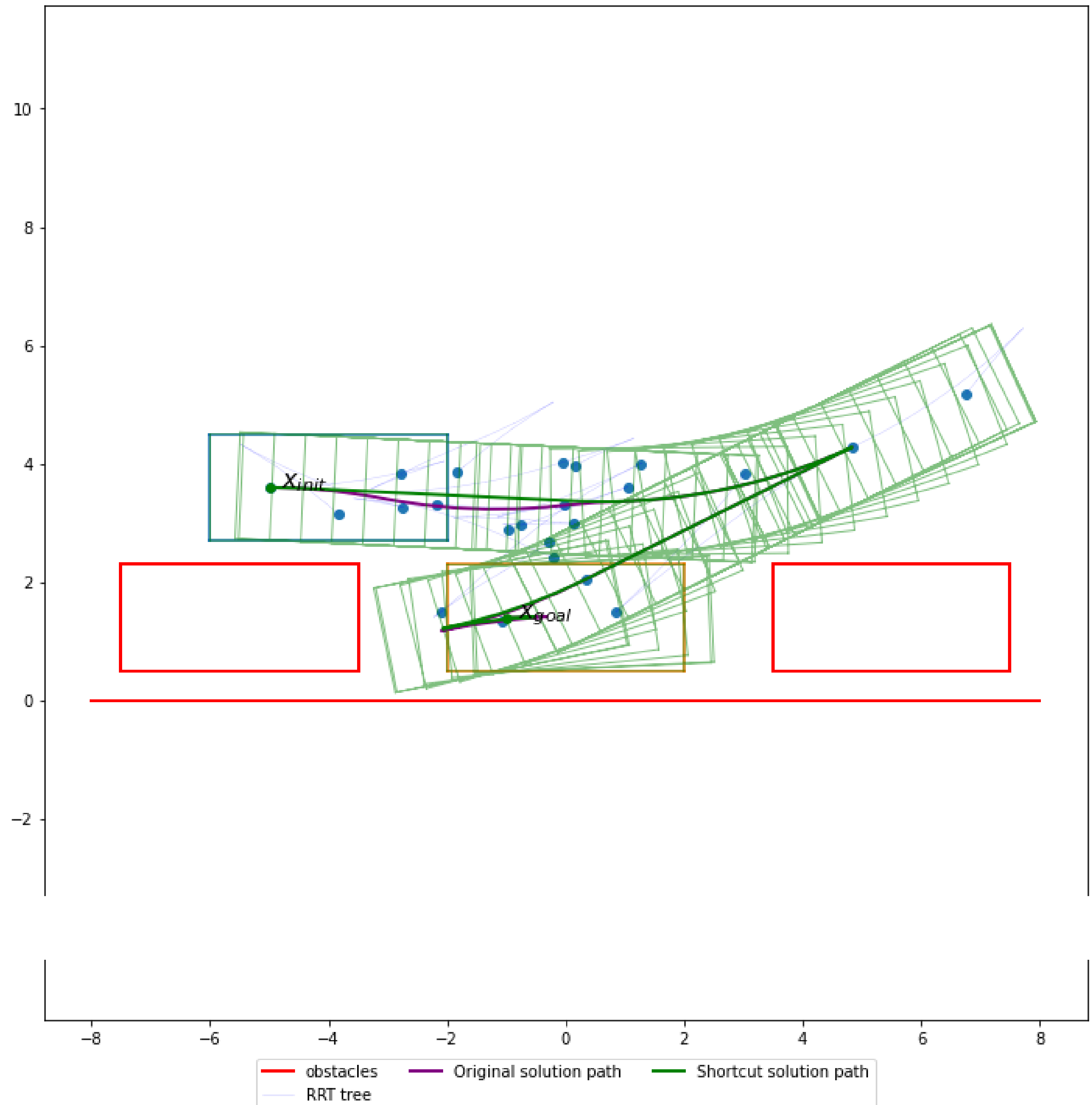
```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

```
x_init = [-5, 3.6, 0]
x_goal = [-1, 1.4, 0]
CAR = np.array([[[-2, -0.9], [2, -0.9]], [[2, -0.9], [2, 0.9]], [[2, 0.9], [-2, 0.9]],
PARKING_SPOT = np.concatenate([CAR + np.array([5.5, 1.4]), CAR + np.array([-5.5, 1.4])
                               np.array([[[-8, 0], [8, 0]]])], 0)

pp_rrt = ParkingRRT([-5, 0, -np.pi / 3], [5, 4, np.pi / 3], x_init, x_goal, PARKING_SI
pp_rrt.plot_problem()
```




```
# RRT is a randomized algorithm; even though this planning problem is feasible, with a
# success is not guaranteed (though we see that with 1000 samples it seems to work mor
# to see the different solutions RRT comes up with, but for debugging you may wish to
# np.random.seed(1235)
pp_rrt.solve(5.0, 1000, shortcut=True)
```

```
True
```



x_{init}
x_{goal}
10
8
6
4
2
0
−2
−8
−6
−4
−2
0
2
4
6
8
obstacles
Original solution path
Shortcut solution path
RRT tree