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# Algorithms for Robotic Motion Planning: from Feasibility to Optimality

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## Objective

The research project is about developing and implementing efficient algorithms for motion planning. The goal is to compute the optimal trajectory for a robot to reach the destination from its initial position.

## Motivation

It usually costs too much human effort to manually design trajectories for robots to reach destinations, which can be infeasible in large environments. Motion planning algorithms alleviate this burden by enabling robots to plan trajectories on their own.

## Models of Trajectory

1. **Artificial Potential Function(APF)**: The sum of an attractive potential pulling the robot toward the destination and a repulsive potential pushing it away from the obstacles. The robot is regarded as having a positive charge, the destination negative while the obstacles are positive. At each point of the encounter, the sum of the forces of attraction and repulsion sets the path.

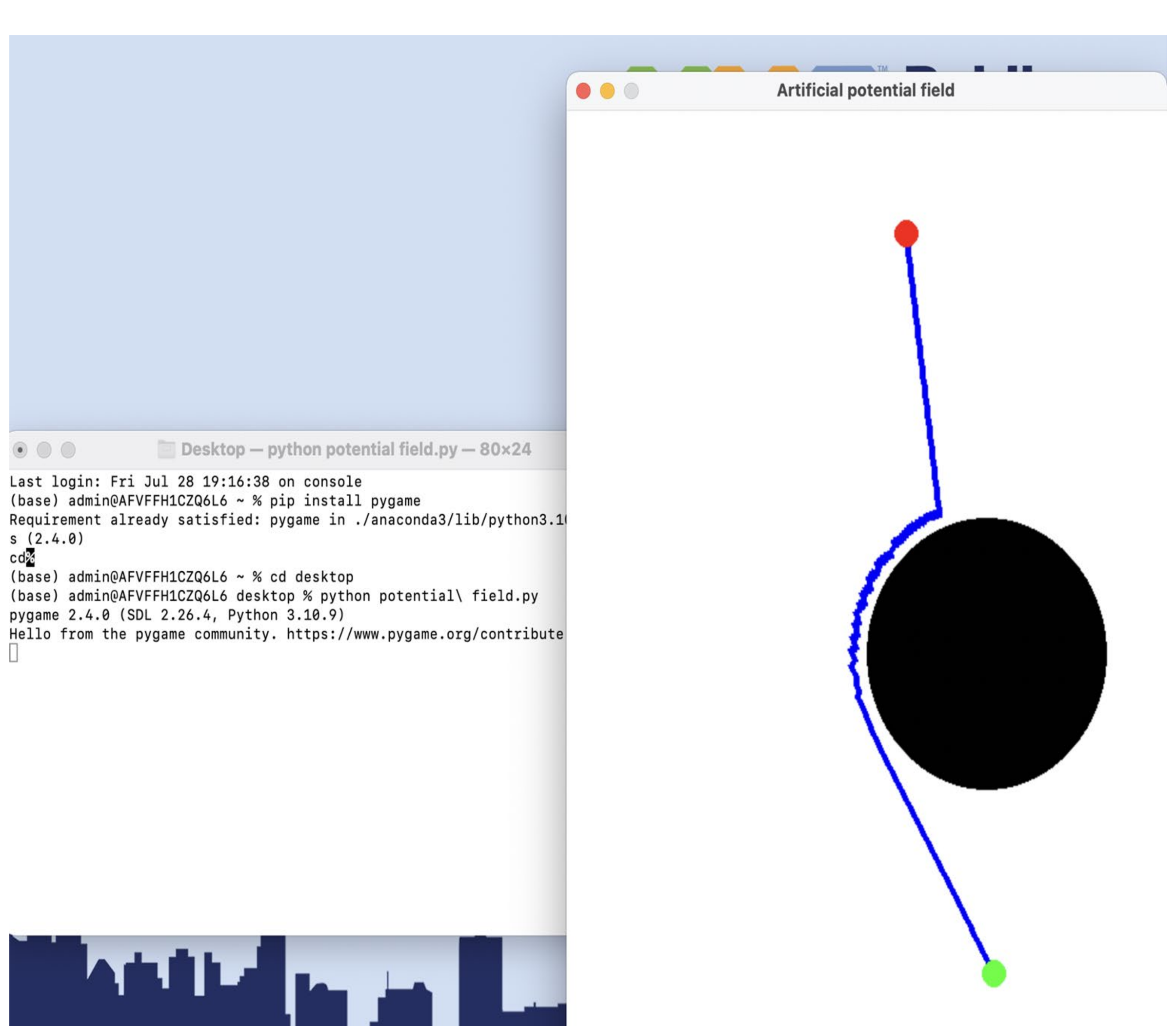


Figure 1: Potential Field
**Red** is the initial point, **black** the obstacle, and **green** the destination
It took 1 sec to set the trajectory.

2. **Rapidly-exploring Random Tree(RRT)**: Construct a tree using random sampling in the whole environment. The tree expands as iterations continue. Node expansion stops and a jagged path is found until the tree touches the destination for the first time.

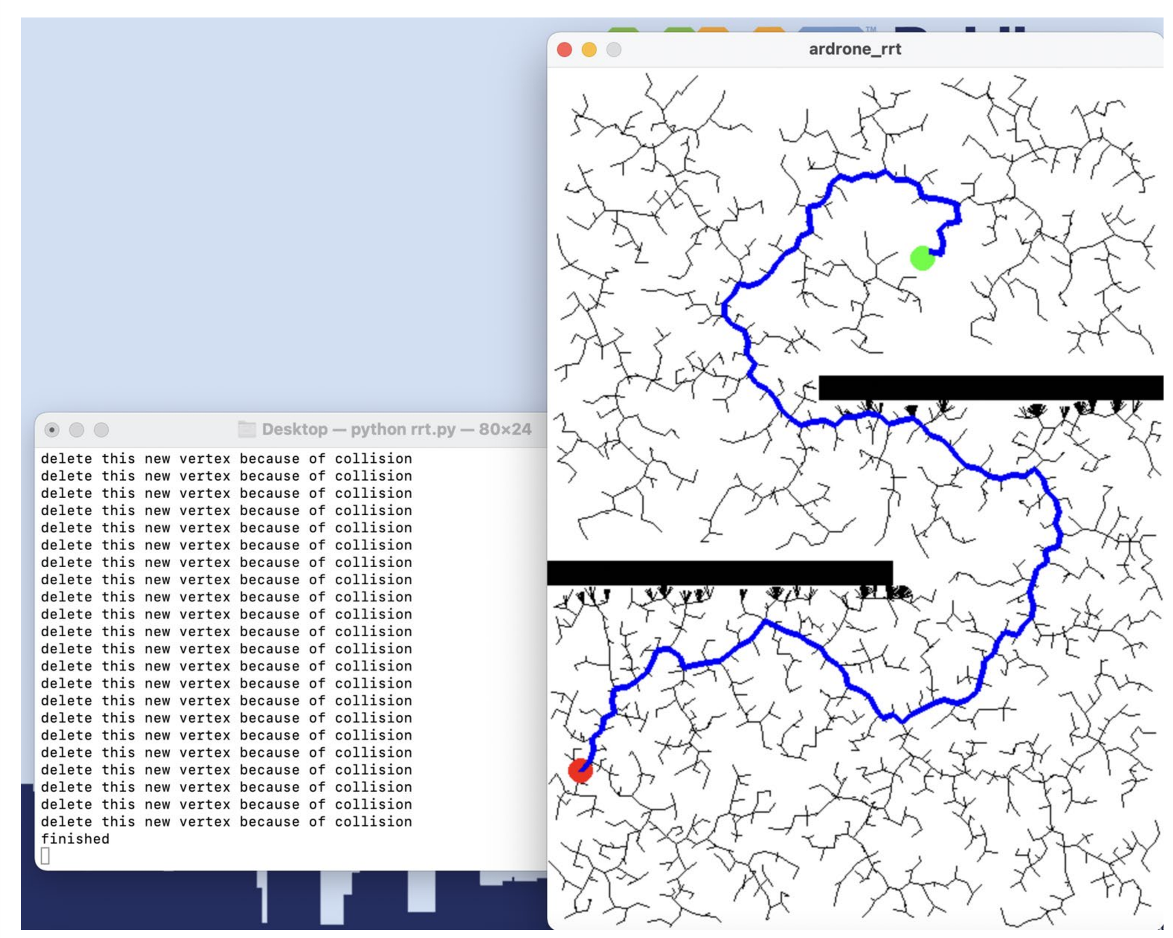


Figure 2: RRT
It took 1 min 41 secs from **red**, the initial point, passed the **black** obstacles to reach the **green** point.

3. **Rapidly-exploring Random Tree Star(RRT*)**: Intelligent sampling continues even when the tree touches the destination. Once a shorter path is found, it performs the path optimization process by running more iterations until it sets an optimal path, less jagged.

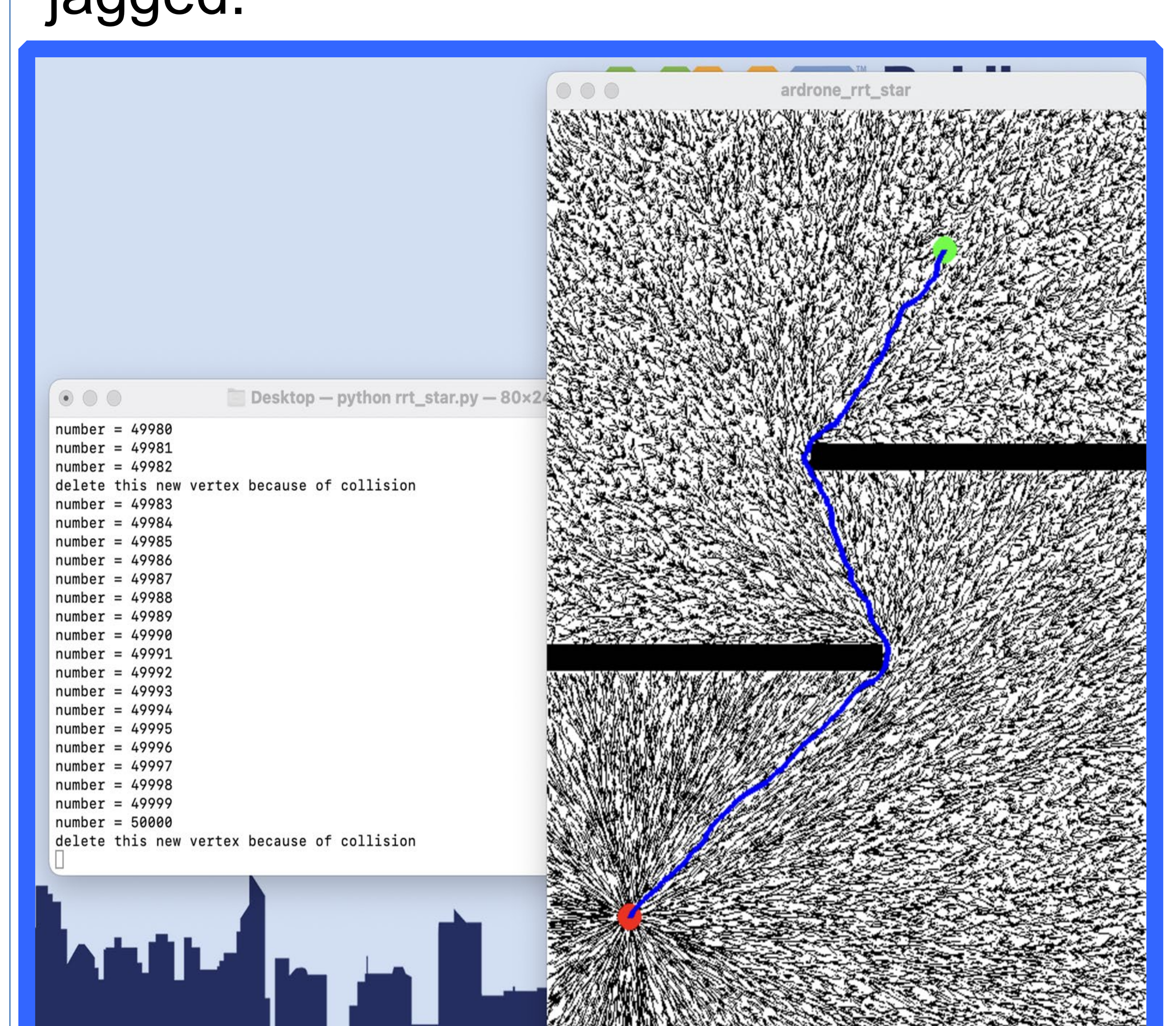
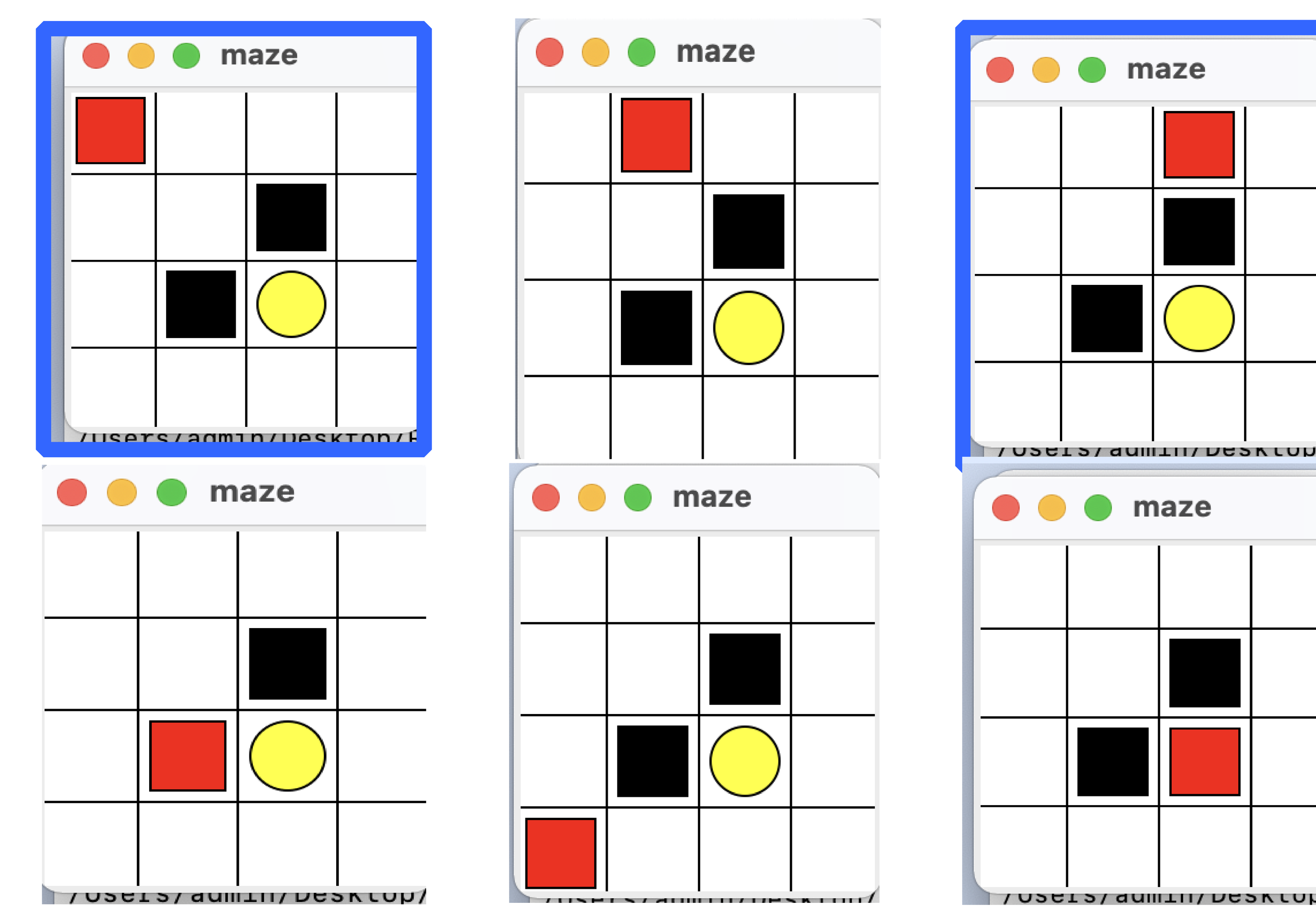


Figure 3: RRT*
It took 1 hour 42 minutes to run 50,000 iterations.

4. **Dynamic Programming(DP):** Using Bellman equation to update the value function(VF) till convergence, which leads to the optimal trajectory with maximum cumulative reward. VF calculates how much future cumulative reward a robot receives if it visits a certain state.



## Analysis of Results

As we need to design an APF for each obstacle, APF works well in simple environments. If the APF is not differentiable from multiple obstacles exerting forces of repulsion simultaneously, the agent may get stuck. When there are multiple obstacles, RRT is more favorable but its trajectory is jagged. RRT* can set an optimal path but it needs a lot of time to run the iterations. DP also offers an optimal path, however, it needs a lot of memory to store the results.

## Implications

While motion planning establishes the exact actions a robot must execute to follow a set path and reach its goal, there is still a lot to learn in terms of how the robot will move(linear, joint, or circular). It will be great to design as optimal trajectory with the help of artificial intelligence and run it in a simulator, like Virtual Box..

The RET for Teachers is funded by the National Science Foundation Grant ECCS:1710859.