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### Implementing RRT\* Path Planning with the Crazyflie Drone

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## INTRODUCTION

### • Background

Crazyfly drone is a compact and agile platform ideal for advanced autonomous navigation. RRT\*, an optimization of the standard RRT, offers efficient path planning in complex environments, enhancing the drone's ability to navigate dynamically around obstacles. This implementation showcases significant potential for applications in areas such as search and rescue, surveillance, and environmental monitoring.

### • Objectives

#### 1. Path Planning with RRT\*:

To utilize the RRT\* algorithm for initial path planning in an area with unknown obstacles for the Crazyfly drone.

#### 2. Obstacle Detection and Adaptation:

To enable the Crazyfly to detect obstacles during its flight using onboard sensors.

#### 3. Dynamic Path Re-planning:

To implement real-time RRT\* re-planning whenever the Crazyfly encounters obstacles, ensuring continuous navigation towards the target.

## METHOD & PROCEDURE

### • Hardware platform - crazyfly

The crazyfly is a compact UAV (see fig.1), which is very suitable for practical testing of algorithms in limited sites, such as this experiment will be RRT\* realized with the crazyfly, the crazyfly is equipped with an ultrasonic ranging module, which can detect the distance of front and back, left and right obstacles, and through the ultrasonic distance and angle, the width of the obstacle can be predicted.

Fig.1 crazyfly

The Flow deck V2 (see fig.2) enhances the Crazyfly 2.X by providing it with the capability to detect motion in any direction. It includes a VL53L1x Time-of-Flight (ToF) sensor, which precisely measures the distance from the drone to the ground.

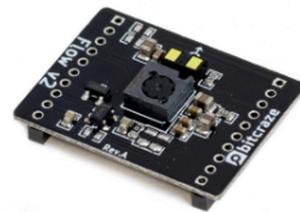


Fig.2 flowdeck

Additionally, the PMW3901 optical flow sensor tracks the drone's movements relative to the ground. These features transform the Crazyfly into a 3D flying robot capable of pre-programmed flights in various directions. They also make it a stable and user-friendly platform for beginners.

## PLAN THE PATH

### • Principles of RRT\*

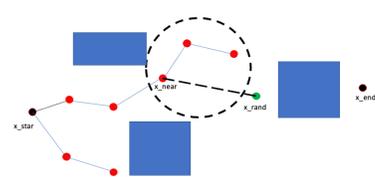


Fig.3: Randomization point

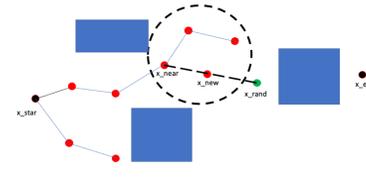


Fig.4: New node

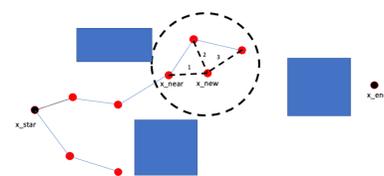


Fig.5: Optimized path

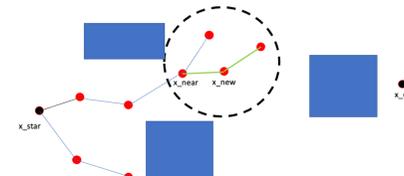


Fig.5: Rewire

#### Algorithm 1: RRT\*

```

1: procedure RRT*(start, goal, obstacleList, area, maxIterations)
2:   Initialize tree  $T$  with start node
3:   for  $i = 1$  to  $maxIterations$  do
4:      $randomPoint \leftarrow getRandomPoint(area)$ 
5:      $nearestNode \leftarrow getNearestNode(T, randomPoint)$ 
6:      $newNode \leftarrow steer(nearestNode, randomPoint, stepSize)$ 
7:     if  $isCollisionFree(nearestNode, newNode, obstacleList)$  then
8:        $neighborNodes \leftarrow getNeighborNodes(T, newNode, radius)$ 
9:        $minCostNode \leftarrow findMinimumCostNode(nearestNode, neighborNodes, newNode)$ 
10:       $addNode(T, newNode, minCostNode)$ 
11:      for all  $neighbor$  in  $neighborNodes$  do
12:        if  $isCollisionFree(neighbor, newNode, obstacleList)$  then  $newCost \leftarrow$ 
13:           $cost(newNode) + distance(newNode, neighbor)$ 
14:          if  $newCost < cost(neighbor)$  then
15:             $parentNode \leftarrow getParent(T, neighbor)$ 
16:             $removeEdge(T, parentNode, neighbor)$ 
17:             $addEdge(T, newNode, neighbor)$ 
18:          end if
19:        end if
20:      end for
21:    end if
22:  end for
23:  end for
24:   $path \leftarrow getPath(T, start, goal)$ 
25:  return path
26: end procedure
    
```

RRT\* pseudocode

### • Experimental process

- **Initial Path Simulation:** Drone takes off and uses RRT\* to simulate a pre-liminary obstacle-free path from start to target.
- **Flight Execution:** Drone follows the initial simulated route.
- **Obstacle Detection:** Ultrasonic sensors scan for and detect obstacles during flight.
- **Obstacle Response:** Drone halts upon detecting an obstacle.
- **Route Replanning:** RRT\* recalculates a new path avoiding the detected obstacle.
- **Adaptive Navigation:** Drone resumes flying, adapting its route based on any new obstacles encountered.
- **Destination Reach:** Continues this process until the target is successfully reached.

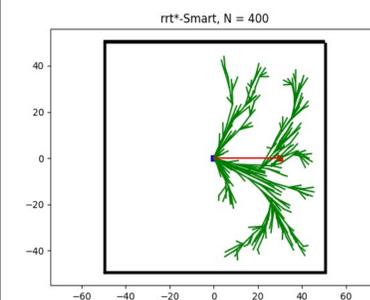


Fig.6: RRT\* approach route without obstacles

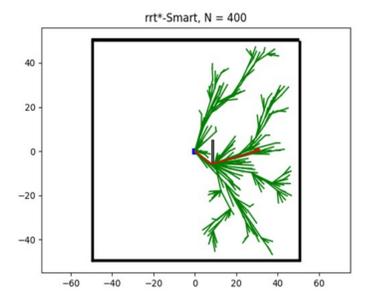


Fig.7: Drone detects part of an obstacle

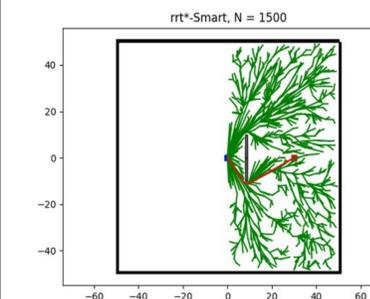


Fig.8: Drones detect more obstacles

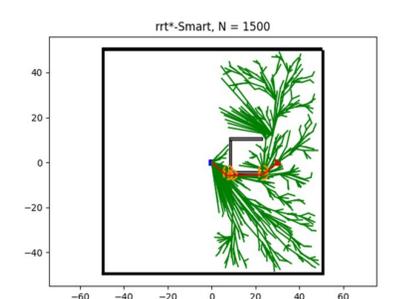


Fig.9: Fly to the target point after several probes

## CONCLUSION

In our drone project, we faced challenges with the drone's limited multitasking capability, leading to time inefficiencies due to segmented path navigation for obstacle detection. This also increased RRT\* iterations and computational load. To overcome these limitations, we plan to implement OptiTrack and ROS for enhanced multitasking and precision control, aiming to streamline the navigation process and reduce inefficiencies.

### • Reference:

S. Karaman and E. Frazzoli, "Incremental Sampling-based Algorithms for Optimal Motion Planning," arXiv preprint arXiv:1005.0416, 2010. [Online]. Available: <https://arxiv.org/abs/1005.0416>