Adaptive Planning for robot navigation using Multi-Layer Planner : ENPM661

Authors: Rahul Karanam , Harika Pendli
Robotics Graduate Students
University of Maryland, College Park
College Park, MD
rkaranam@umd.edu,hpendli@umd.edu

I. Introduction

The process of establishing the path to the target point and the process of following the path established are both required when we want the mobile robot to move from its current position to the target point.

Path planning can be separated into two types: global and local path planning. The creation of a complete path to the target point was referred to as Global Path Planning, and the optimum path may be computed.However, because of the open loop's properties, it was difficult to use this technology in a variety of contexts that required sensor feedback.

The purpose of the Local Path Planner is to allow the robot or agent to adapt to a new environment. It assists the robot in following the path (destination) without prior knowledge of the target and avoiding obstacles by utilizing its sensory information cognitively. Although it can attain the goal, it is not necessarily the optimal path.

This report explains the process of implementing a multi layered planner for navigation of multi-robots in a cluttered environments.

First section will explain about process of implementing RRT(Rapidly Random Trees) as a global planner.Later sections will explain about using Artificial Potential Field(APF) as a local planner.

Later sections discussed about combining these two planner into a multi-layered planner which will be used for navigating multi-agents in a static and dynamic environments.

A. Background

Multi-agents or robots have traditionally been employed for formation, loading, crossing restricted tunnels, and a variety of other tasks. The agility of these robots in such tough terrains and settings has been extensively researched. The ability to navigate and direct these robots in unstructured environments, as well as collaborate with other multi-agent systems, can be used in a variety of applications. These can be utilized as first responders in emergency circumstances, infrastructure monitoring, package delivery, precision agriculture, disaster response, and hospitality services like entertainment, for example.

B. Problem Statement

Navigation of Multi-agents in a cluttered environment and avoiding obstacles is a difficult task.We propose a two-layered path planning approach which avoids dynamic and static obstacles using potential fields.It follows a leader-follower network with a predefined formation space and adapts dynamically to the environment.

II. Global Planner

Implementation of Rapidly exploring random tree:

Rapidly-exploring Random Trees (RRT) is a sampling-based motion planning algorithm. It is an algorithm capable of exploring the space quickly while being able to deal with complex obstacles as well. The RRT algorithm was first introduced in 1998 in the paper []. As every other motion planning algorithm, RRT provides a feasible path from initial state to goal point by using a tree or graph type data structure. The configurations produced by this tree spreads out through the entire space and is able to do so while taking into non-holonomic constraints (kinematic differential constraints and dynamical constraints) and high degrees of freedom.

An RRT tree grows from its root, given by the start configuration, and continues by generating random samples from the environment or space. For every random sample drawn, a connection between this random point and the nearest node in the tree is attempted. If the connection laid is feasible, in this context it means, the connection shouldn't pass through obstacle space, while constantly abiding by the constraints, a new node at a unit incremental distance in this connection is added to the tree configurations.

Please refer figure-1 figure-2 for the RRT output on different obstacle space.

Also, the tree preferentially expands towards large areas which have remained unsearched.The inputs given to an RRT algorithm in configuration space C are Initial configuration qinit or the start point, number of vertices in RRT K, incremental distance δ q, and the output is an RRT graph

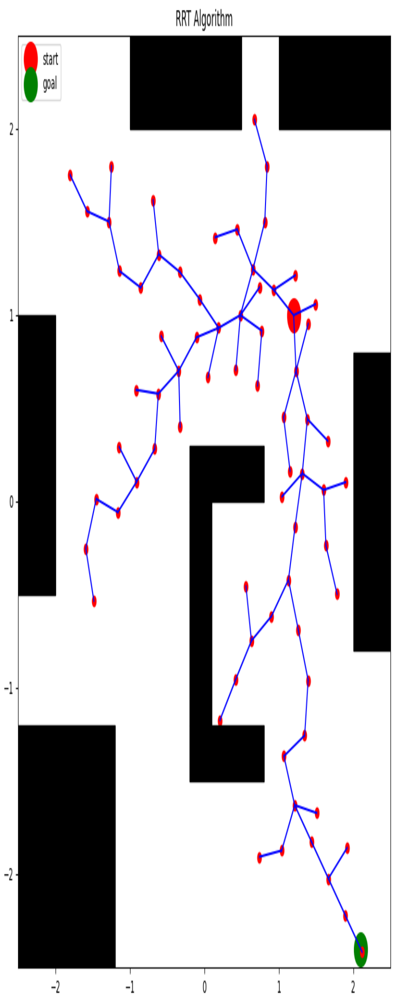


Fig. 1: RRT algorithm on a sample configuration space

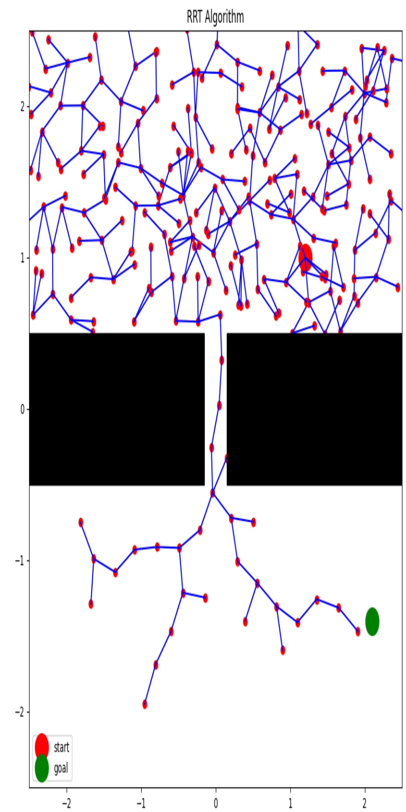


Fig. 2: RRT algorithm on a sample configuration space

which can be queried for any required goal state.

We have shortened the path generated by the RRT in order to reach the goal faster and also to compare it with the local planner path.

Please refer to figure 4 for showing the difference between the generated path and the shortened path of the RRT.

III. Local Planner

Implementation of Artificial Potential Field:

The goal of this section is to implement a local planner using the concept of potential field. These methods basically works as a smooth function, where high values indicate that the robot is near to the obstacle and lower values indicate it is far from the obstacle.

Basically there are two types of potential functions , repulsive and attractive. Attractive potential is the function or the potential where the which can be constructed using the distance between the current position and the goal position.Please refer to equation - 1 representing the attractive potential function.Please refer figure - 2 for a sample configuration space.

$$U_{att} = \frac{1}{2}\eta\left((x-x_g)^2 + (y-y_g)^2\right)$$

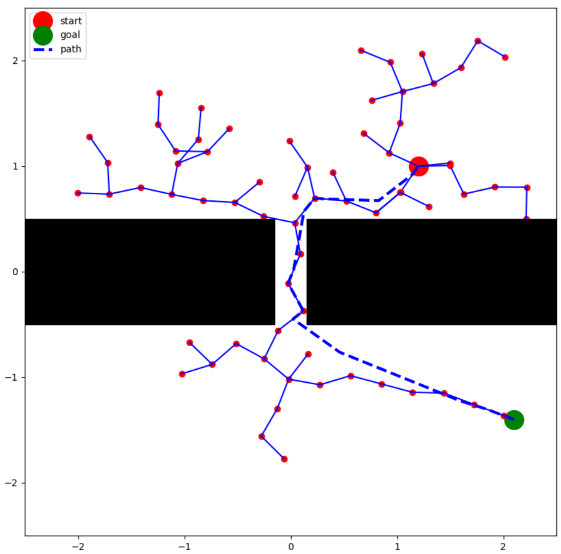
In the above equation , xgoal,ygoal is the goal coordinates , x,y is the current position of the robot. $\eta is the scaling factor$

Attractive potential tells the robot to drive towards the goal whereas repulsive function helps to avoid obstacles.

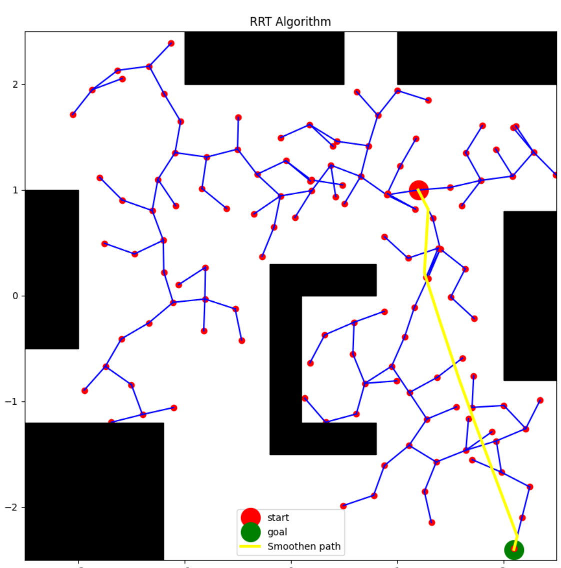
Please refer to figure 4 for the output of attractive potential on a sample configuration space.

$$U_{rep} = \begin{cases} \frac{1}{2}k_r\left(\frac{1}{\rho_O} - \frac{1}{r_O}\right)^2 & \text{if } \rho_O \leq r_O \\ 0 & \text{if } \rho_O > r_O \end{cases}$$

The closest distance to the obstacle is given by the below equation.



(a) RRT algorithm output with shortened path - 1



(b) RRT algorithm output with shortened path - 2

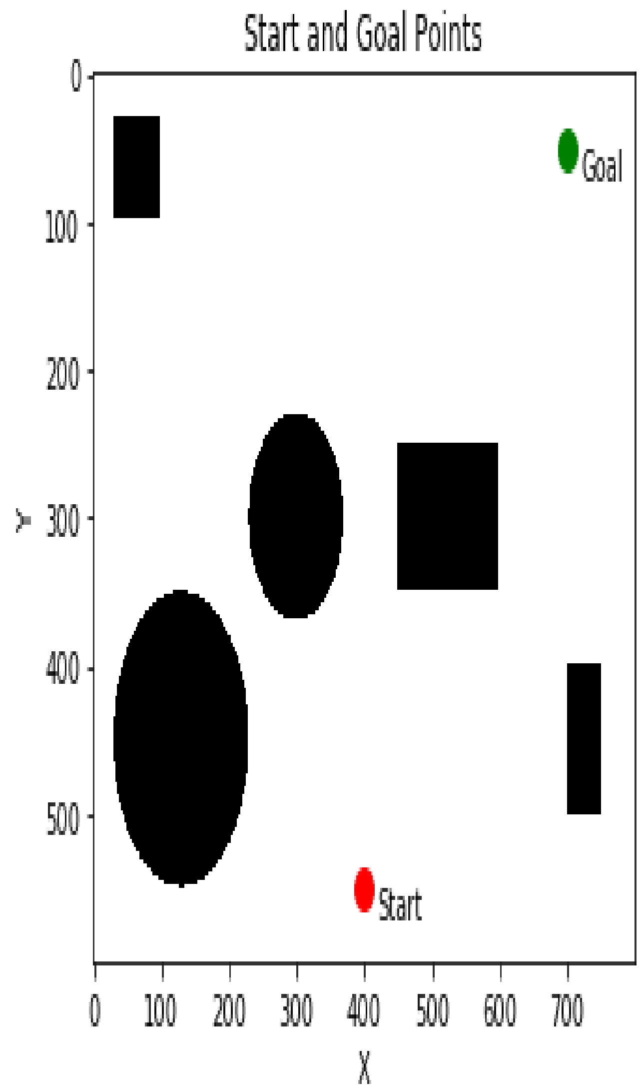


Fig. 4: Sample Configuration for APF

$$\rho_O = \sqrt{x_{or}^2 + y_{or}^2}$$

As per equation - 2 , repulsive potential function returns the distance to the closest obstacle region from a given point in the configuration space C.

Please refer to figure 4 for the output of repulsive potential on a sample configuration space.

η - Constant Scaling Factor

d_0 - It controls the influence of repulsive potential

The total potential field can be equated to the sum of attractive and repulsive potential.

$$F_{APF} = F_{att} + F_{rep}$$

Please refer to figure 6 for the output of total potential(APF) on a sample configuration space.

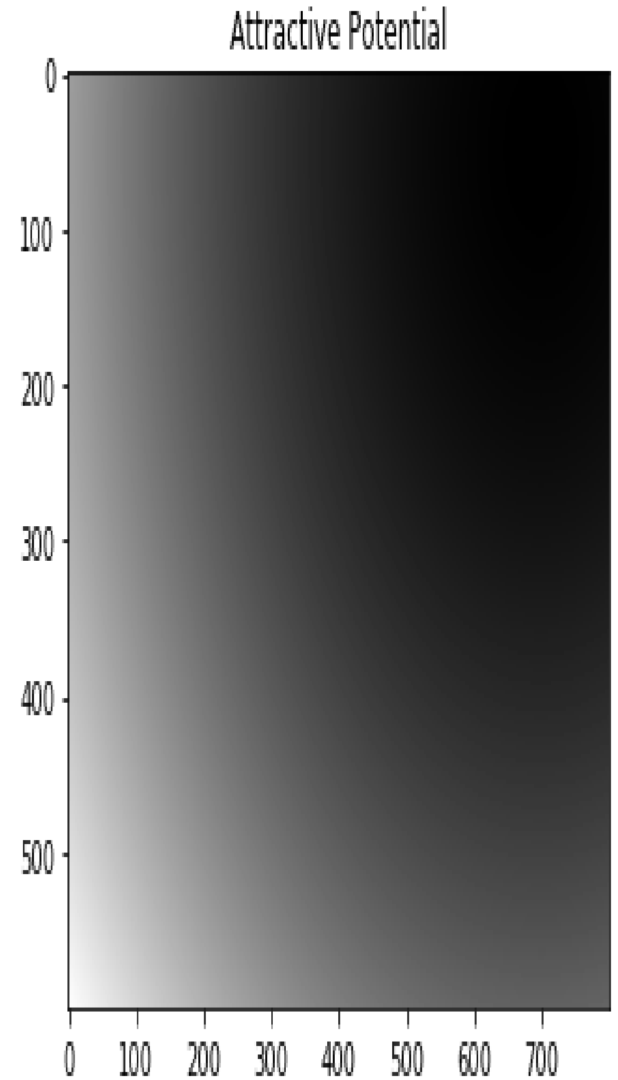


Fig. 5: Attractive Potential

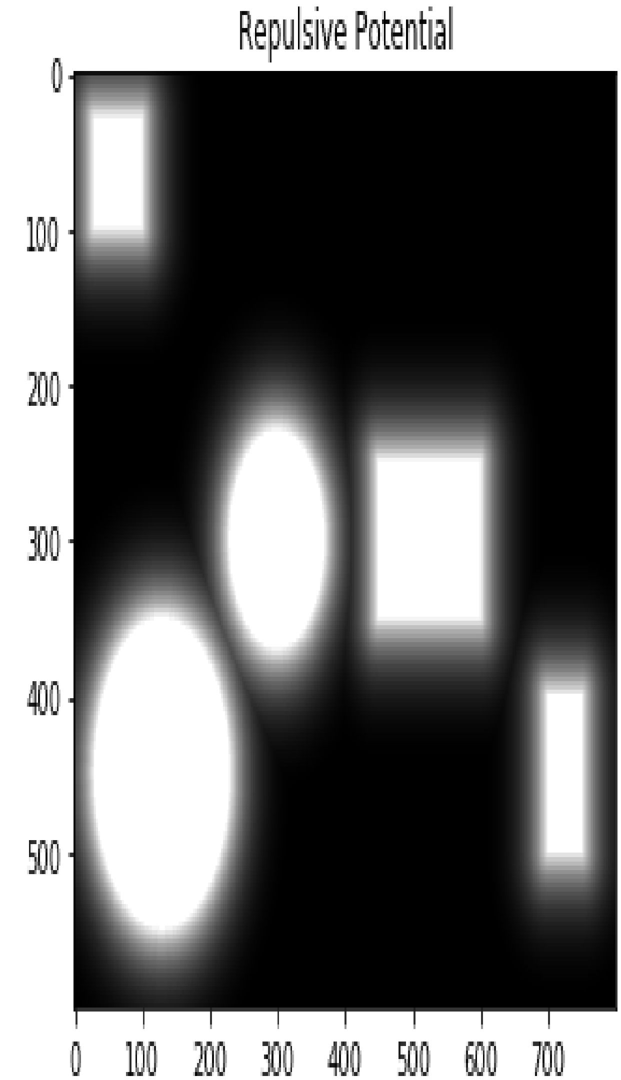


Fig. 6: Computing Depth using Disparity

The way APF works is to find a path using the total potential function and its partial derivative. While the robot position is not close to the goal, we calculate the gradient of the total potential function and choose the direction of the robot velocity in the negative direction and follow the path until you reach the goal while avoiding obstacles.

Please refer figure 7 for a sample path planned using APF.

The only drawback of using APF as a path planner is the function gets stuck at local minima when the object and goal are very close to each other or there are narrow passage where the robot might think lower potential and tries to get stuck as it thinks that position is the optimum region.So in-order to avoid these , we will be combining it with RRT.

We will be extending this local planner along with our global planner into a multi-layered planner.

IV. Layered Planner

In previous sections, we have discussed RRT and APF. We have also mentioned that RRT plays the role of global trajectory generation and APF is the local trajectory generator. The RRT lays the global trajectory that is the initial path for the leader-drone and APF allows for the path correction for each robot in the swarm path while following the leader's lead while maintaining the pre-described formation. This section is devoted to explaining the layered planner which combines the above-explained algorithms, RRT and APF.

We will be using RRT (global Planner) to generate a roadmap from the start to the end goal position which is being shortened to avoid sharp turns around the obstacles.This optimal path is being given as a waypoints to our multi agents in order to follow the leader till the end goal.

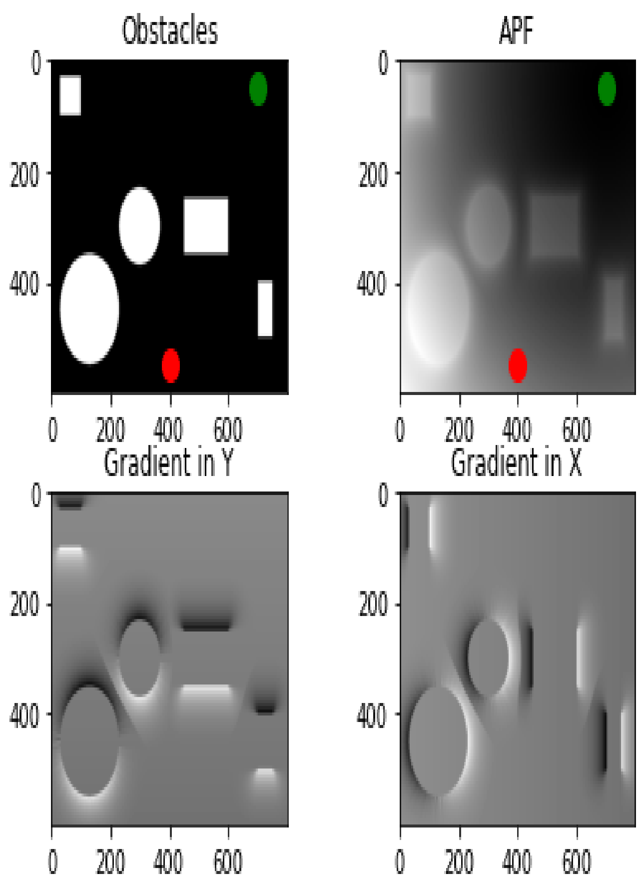


Fig. 7: Gradient output

Layered planner is a combination of RRT as well an APF planner. First, we generate a graph in the obstacle-ridden environment with the Rapidly-exploring Random Tree algorithm. From this graph, we generate the first approximation for the global path from start to goal. This path is optimized by using a path shortening algorithm which becomes the final global path for the leader. The local trajectory is generated by using APF algorithm which ensures the robots avoid obstacles and other moving objects in real-time.

A major drawback of APF is the local minimum problem which is the main reason for not choosing APF as a global planner in practical scenarios as it is not able to traverse non-convex obstacles. Therefore, in this layered planner, APF is used to plan the robot's position locally between the way points. If we can run this algorithm in real-time, APF can also support anti-collision from dynamic obstacles. APF is also able to tackle situations where the environment might have changed after global trajectory has been set. This layered planner also finds its application in navigation where the leader uses the global path and the geometric formation among the swarm is maintained with APF.

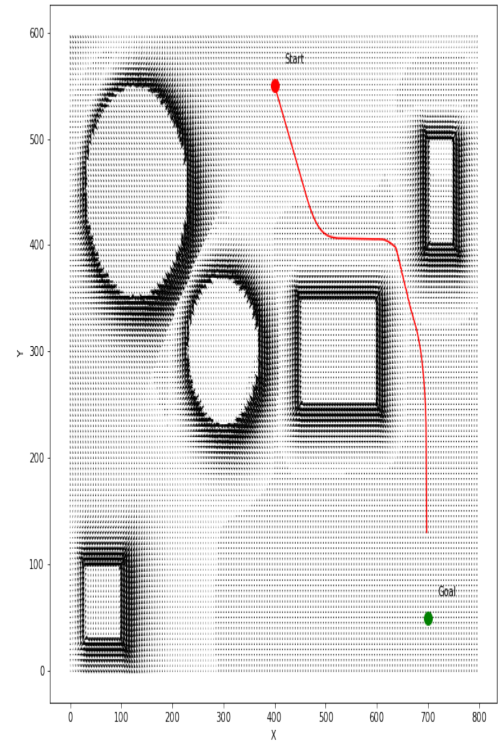


Fig. 8: Path Planned using APF

A. Experimental Setup

We have tested our algorithm on two configuration space , one with too many obstacles and one with less obstacles but very narrow regions between the obstacles which will make the robot very difficult to follow the path.

Two obstacles configuration space were considered for experimentation. Tested with different number of robots

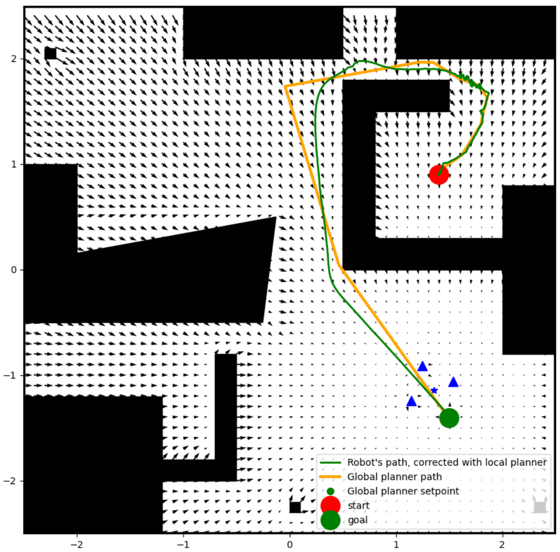
Please refer figure 9 showing the different configuration space.

B. Simulation Results

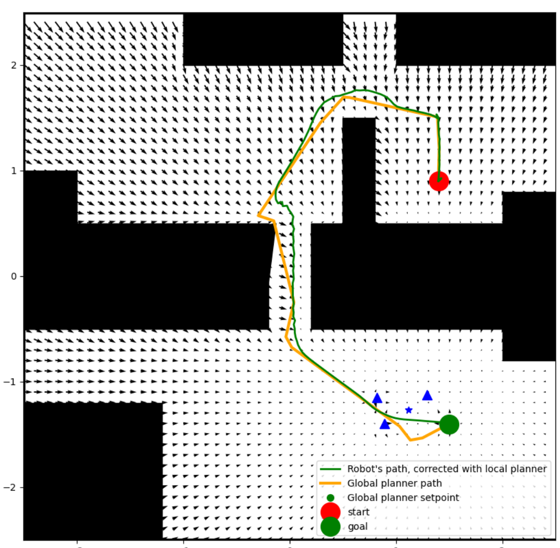
Please refer to the below figures representing the output of our proposed algorithm on single robots and multiple robots.

Problems faced and Solutions

- First the time complexity of the algorithm was too large and it initially took longer time for implementing RRT in a narrowed obstacle space
- The algorithm worked well with configuration space where there connections are less narrow.
- In some cases, where the obstacle space is cluttered , the robot tends to get stuck along the obstacle and tries to cross the obstacle which is not expected. I had to increase the gap between the obstacle in order to compensate the above error.
- The path generated by RRT was not suitable for path following as it has sharper turns, in order to reduce that we have shortened the path.

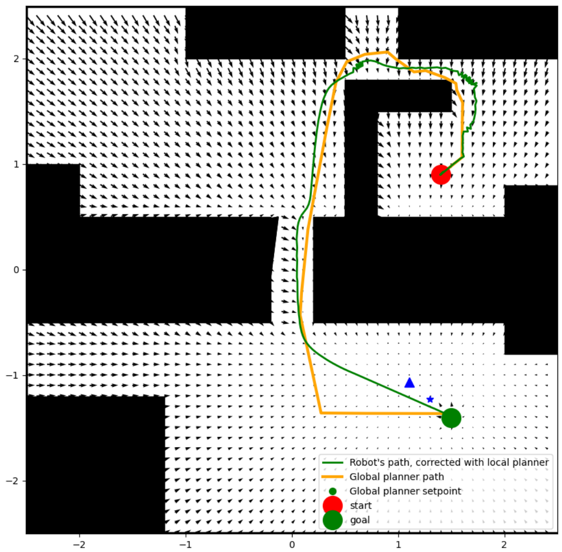


(a) Configuration Space - 1

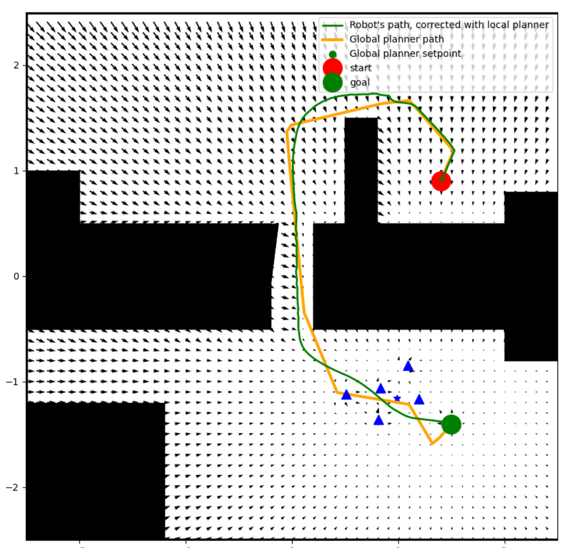


(b) Configuration Space - 2 Narrowed Obstacles

Fig. 9: Stereo Matching Rectification output for Dataset - 1

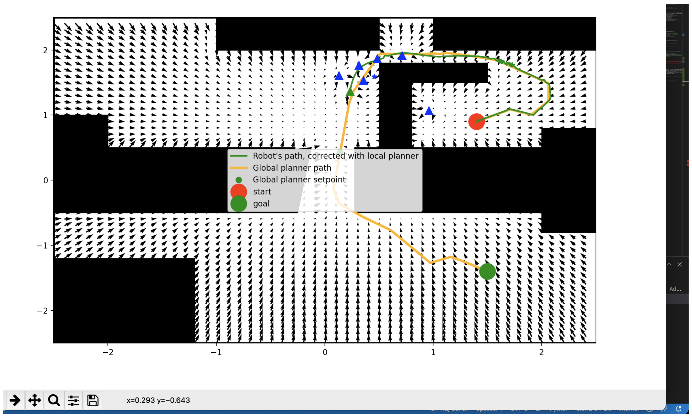


(a) Layered Planner Output with one robot



(b) Layered Planner Output with five multi robots

Fig. 10: Output of our Proposed Algorithm



(a) Robot navigation failed following the leader due to narrowed passage - 1

(b) Robot navigation failed following the leader due to narrowed passage - 2

Fig. 11: Failed Test Cases of our proposed algorithm

V. Further Thoughts

In this project, we implemented Rapidly-exploring Random Trees and Artificial Potential Field path planning algorithms. Combining these two planners, we have demonstrated a fairly new planner called Layered Planner. Loosely speaking, Layered planner involves RRT as its global planner and APF as its local trajectory planner. We have simulated the results with a leader and follower swarm robots as they traverse in an obstacle-ridden space from start to goal position.

This algorithm can be further developed by adding more robots to the swarm and involving drone dynamics. Progress can be made by introducing random dynamic obstacles into the environment. Unlike the uniform obstacles presented in the simulation. To be even more ambitious, all of this can be developed to work in 3d world and implementation on real drones.

A. Github

Please refer to this github repository for the above code base.

Github: https://github.com/karanamrahul/Adaptive-Layered-Planner.git

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