Probabilistic Road Map mixed Artificial Potential Field Path Planning for Non-Holonomic Robots in Dynamic and Off-Road Terrain

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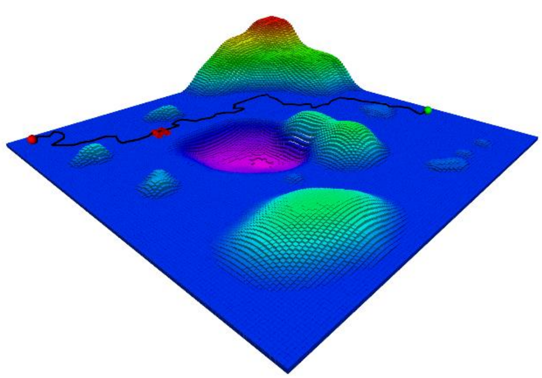
GitHub: https://github.com/Prat33k-dev/PRM-Blended-Potential-Field-Path-Planning

***Abstract*— Probabilistic roadmap (PRM) algorithm generates graphs to perform path planning with complex constraints and high dimensions but has some limitations in situations like narrow pathways and environments with dynamic obstacles. This drawback of PRM is usually solved by increasing the number of randomly generated sampling points. However, too many sampling points will increase the computational complexity resulting in poor performance. Hence to overcome these limitations PRM with potential fields can be implemented. Potential field can be generated for the workspace, will help determine the complexity of workspace and adequate number of sampling points required, and then ensure high density of sampling points around the obstacles by implementing a regional sampling strategy.**

Keywords—robotics, path planning, artificial potential field, probabilistic roadmap, simulation, heightmap, grid map.

I. Introduction

With the increasing use of robots in military, industrial, aerospace, and other off-road terrains the path planning gets challenging as the environment size increases. Most traditional robot path planning algorithms use a predefined map of specified dimensions. Implementing an algorithm without dimensional limitations will be beneficial as it could be used for both 2D and 3D spaces.



Among the Commonly used path planning algorithms like A-star (A*), Rapidly Exploring Random Tree (RRT) and PRM, PRM transforms the workspace into topological space and eliminated the dimensional constraint. Once the topological roadmap is generated by PRM, it can be used until the environment changes which increases makes the algorithm efficient even for large workspaces.

PRM possesses a limitation working with environments containing narrow pathways and dynamic environments as the randomness in sampling points may leave the pathway untraversable. This method ensures increasing the density of sampling points near obstacles and narrow pathways without taking a huge number of sampling points and keeps the computational complexity low.

Artificial Potential Field algorithm (APF) requires low computation, rapidly reacts to the environment, and independent of dimensions of the workspace, making it suitable for blending with PRM to improve its narrow pathway limitations. The approach uses the repulsive forces of the obstacles to determine the areas of narrow pathway and increase the density of sampling points around them.

II. PRM Mixed Artificial Potential Field Path Planning

A. *Determine number of sampling points using adaptive solution*

a) Repulsive potential:

Adaptive sampling point method based on obstacle density helps limit the number of sampling points to match workplace obstacle density, preventing the excessive number of sampling points resulting in inefficient roadmap construction and , too many sampling points will increase the computational complexity, which results in poor performance.

For each point q in the map the repulsive potential $U_{rep}(q)$ generated by obstacle q_o is calculated using

$$u_{\mathrm{rep}}(q) = \begin{cases} \frac{1}{2} k_{\mathrm{rep}} \left(\frac{1}{q - q_0} - \frac{1}{p_0} \right)^2 & q - q_0 \leqslant p_0 \\ 0 & q - q_0 > p_0 \end{cases} \quad (1)$$

Where p_o is the repulsion field range of the obstacle.

b) Determine Number of Sampling Points:

Number of sampling points N_{pts} can be calculated using round up equation (2)

$$N_{pts} = \alpha \mathrm{DM} \tag{2}$$

Where α is the coefficient of the working space and DM is the ratio of average potential in the map and average potential in the map with full of obstacles.

As a result, the number of sampling points adapts to the density of obstacles in the work environment.

B. *Regional sampling strategy*

Repulsive potential was calculated for each position in open area in the map using equation (1). Using bounding range for open area and obstacle region sampling point can be distributed in the map.

This distribution strategy provides excellent connectivity of narrow pathways by ensuring high density of sampling points around obstacles which are the cause of narrow pathways overcomes the limitation of PRM and improves the connectivity of graph.

III. Simualtion And Results

a) Environment setup

Simulation environment was created using heightmap with dimensions of 20 m × 20 m with varying terrain and obstacles as shown in **Fig. 1**. The path planning algorithm was implemented on the Clearpath Robotics-Husky UGV, a four-wheel skid steer drive platform.

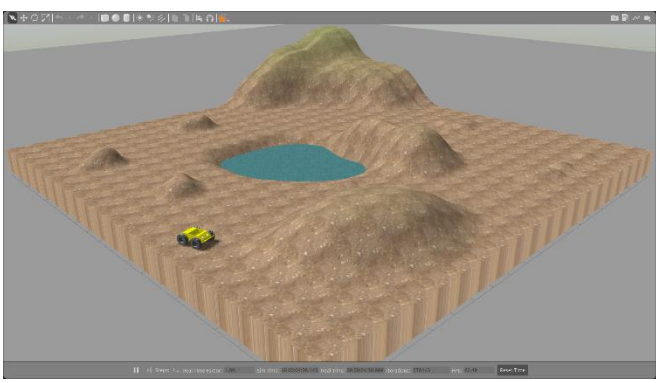
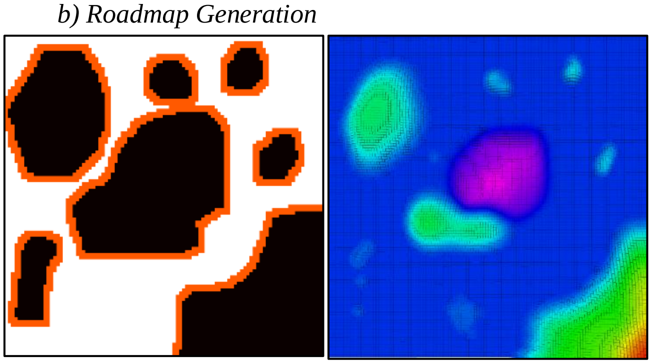


Fig 1: Gazebo world

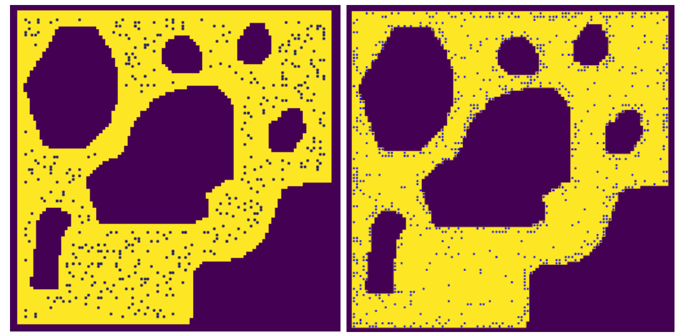
b) Roadmap Generation



a) b)

Fig 2: a) Potential field around obstacles
b) potential field heatmap

An occupancy grid map of the environment was generated which is used to compute the potential field map taking k_{rep} =100 and p_0=5, that shown in **Fig. 2**. The potential field map displays smaller potential field in the area far from the obstacle, while the large potential field is seen around the obstacles.



a) b)

Fig 3: a) Traditional PRM sampling points
b) PRM-APF blend sampling points

Fig. 3a displays the graph generated by traditional PRM (N_{pts}= 980). The distribution of sampling points generated by PRM-APF blended algorithm is shown in **Fig. 3b**. (λ = 2000, and N_{pts}= 980), substantiates the high density of the sampling points near obstacles. Furthermore, as obstacle density increases, the number of adaptive sampling points increases accounting for the narrow pathways generated, improving the PRM connectivity.

c) Planning

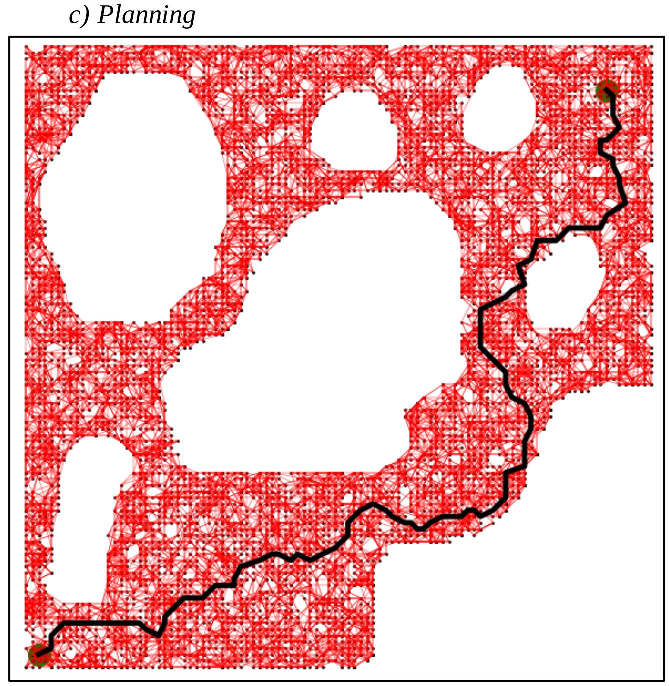


Fig 4: Path planned by PRM-APF blend algorithm

Dijkstra algorithm was used to find the path providing the PRM graph. **Fig. 4** displays the path generated with PRM-APF algorithm with start and goal coordinates as *(1,1)* and *(19,19)*. The path coordinates were saved to *.csv* file. These coordinate commands were given to controller to move the Husky robot.

IV. Conclusion and Future work

The PRM-AFP blended algorithm significantly improves the narrow pathways path planning and the graph connectivity. The algorithm was 97% successful in generating paths for the tested scenarios. For future work we plan to accommodate local reconstruction of roadmap based on dynamic changes in the map instead of generating the whole graph again.

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