Milestone Report: Integrating Machine Learning into Path Planning for Autonomous Systems

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Introduction

The pursuit of autonomous navigation systems capable of operating in complex, dynamic environments is at the frontier of current robotics research. Our project, "Integrating Machine Learning into Path Planning for Autonomous Systems," aims to contribute to this field by developing machine learning models that enable more efficient and robust path planning for autonomous agents.

Motivation

The primary motivation for this project is the critical need for reliable autonomous navigation systems across various sectors, including transportation, logistics, and public safety. Current path planning methods struggle with unpredictability and dynamic changes in real-time environments. Traditional pathfinding algorithms like Dijkstra and A* have shown limitations in environments that change in real-time. In our pursuit of a more robust solution. Following this, we will investigate reinforcement learning algorithms; we are exploring the RRT family of algorithms known for their proficiency in complex and dynamic spaces and then play around with reinforcement learning algorithms like Deep Q- Learning in dynamic environments to endow our navigation systems with the ability to learn and adapt from interactions with their environment.

Method

Machine Learning Algorithms

Our project will explore the following approaches:

Rapidly-exploring Random Tree (RRT): A foundational algorithm for navigation in unknown environments, which we believe could overcome some of A*'s shortcomings.

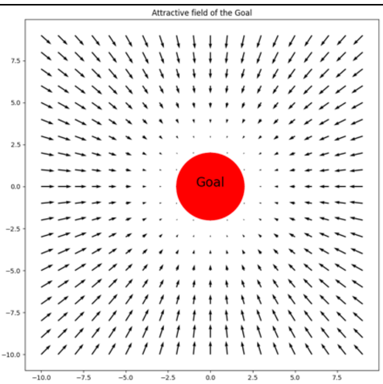
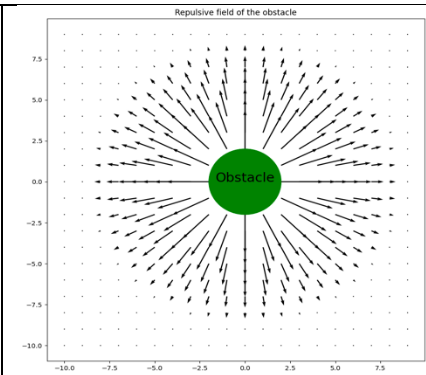
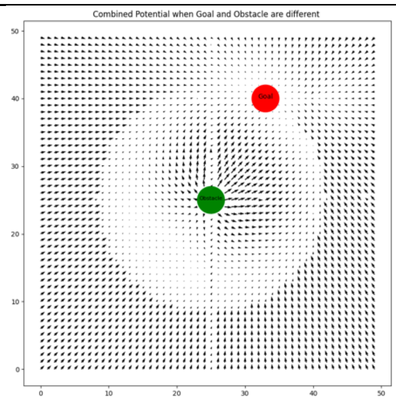
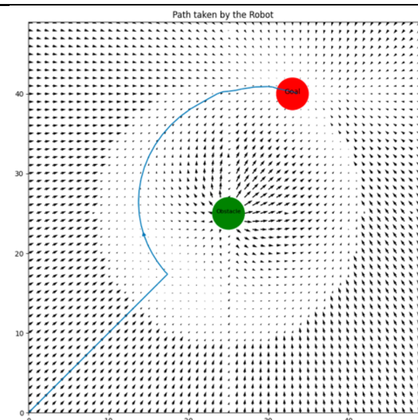
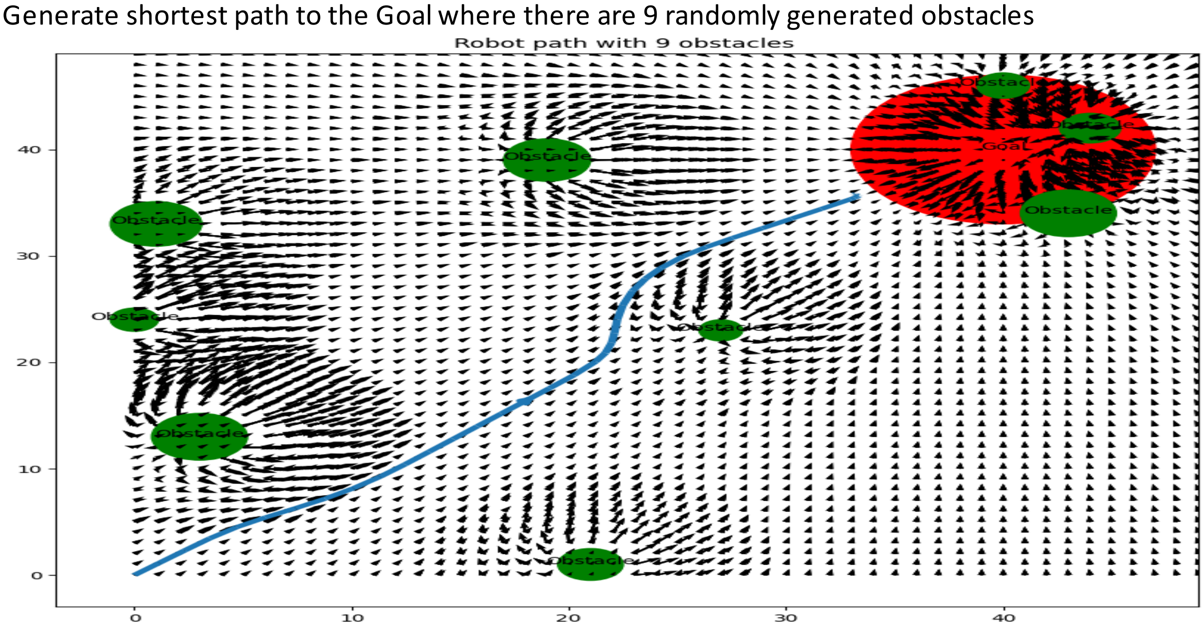
RRT Variations: We will explore modifications of the standard RRT, such as RRT* and LQR-RRT, Linear-quadratic regulator rapidly exploring random tree (LQR-RRT) is a sampling based algorithm for kinodynamic planning, which promise better performance in terms of path optimality and computational efficiency.

Reinforcement learning algorithms such as deep q-learning or monte-carlo tree search algorithms can help us find optimal paths self-learning with a cost-reward system.

Preliminary Experiments

For starters, we tried re-creating methods from a few papers we found online. We will move to a dynamic environment with more advanced algorithms after this. We are currently struggling with creating our own dynamic environment, so we might end up using the gymnasium environment.

Local Path Planning Using Virtual Potential Field

<table>
<tr><td>Attractive field of the goal</td><td>
</td><td>Repulsive potential field of the obstacle</td><td>
</td></tr>
<tr><td>Combining Potential when Goal and the Obstacle are present</td><td>
</td><td>Generate path to reach the Goal</td><td>
</td></tr>
<tr><td colspan="4">Generate shortest path to the Goal where there are 9 randomly generated obstacles

</td></tr>
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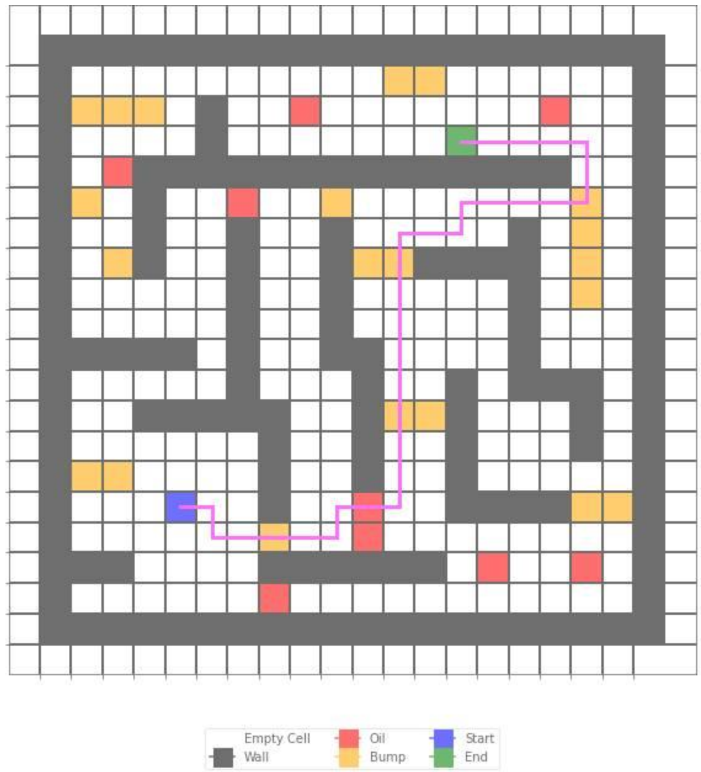
We tried the algorithm in a static environment. A* Algorithm Experimentation: We have concluded our experiments with the A* algorithm, which, despite its efficiency in static path planning, does not reflect to dynamic scenarios. Our analysis indicates that A*'s performance is limited by its reliance on heuristics that do not adapt in real-time to environmental changes.



The next phase of our project involves:

RRT Implementation: Developing and testing RRT and its variations to assess their suitability for our path planning needs in complex and dynamic environments.

Reinforcement Learning Integration: After evaluating RRT, we will begin integrating RL algorithms, adjusting their design and parameters to suit the specific challenges of our navigation tasks.

Training and Comparative Analysis: We will train the selected RL models and conduct a comparative analysis against the RRT-based algorithms, examining their adaptability, learning curves, and efficiency in real-time decision-making.

Conclusion

The shift to RRT and subsequent RL algorithms represents a strategic move towards achieving greater adaptability and intelligence in autonomous navigation. By systematically exploring these algorithms, we aim to identify and develop a superior path planning approach that can handle the dynamic and unpredictable nature of real-world environments effectively.

Contributions:

For the completion of the milestone, both Tahmid Zaman Tahi and Mashrur Wasek, collaborated equally. There were several papers / articles that we each divided amongst us and read to mimic the papers in hardcode. There were several debugging sessions and long nights at the library to get the algorithms up and running. We will equally divide work for the next steps as well.