DEEP RRT*

ENPM 661: Planning for autonomous robots

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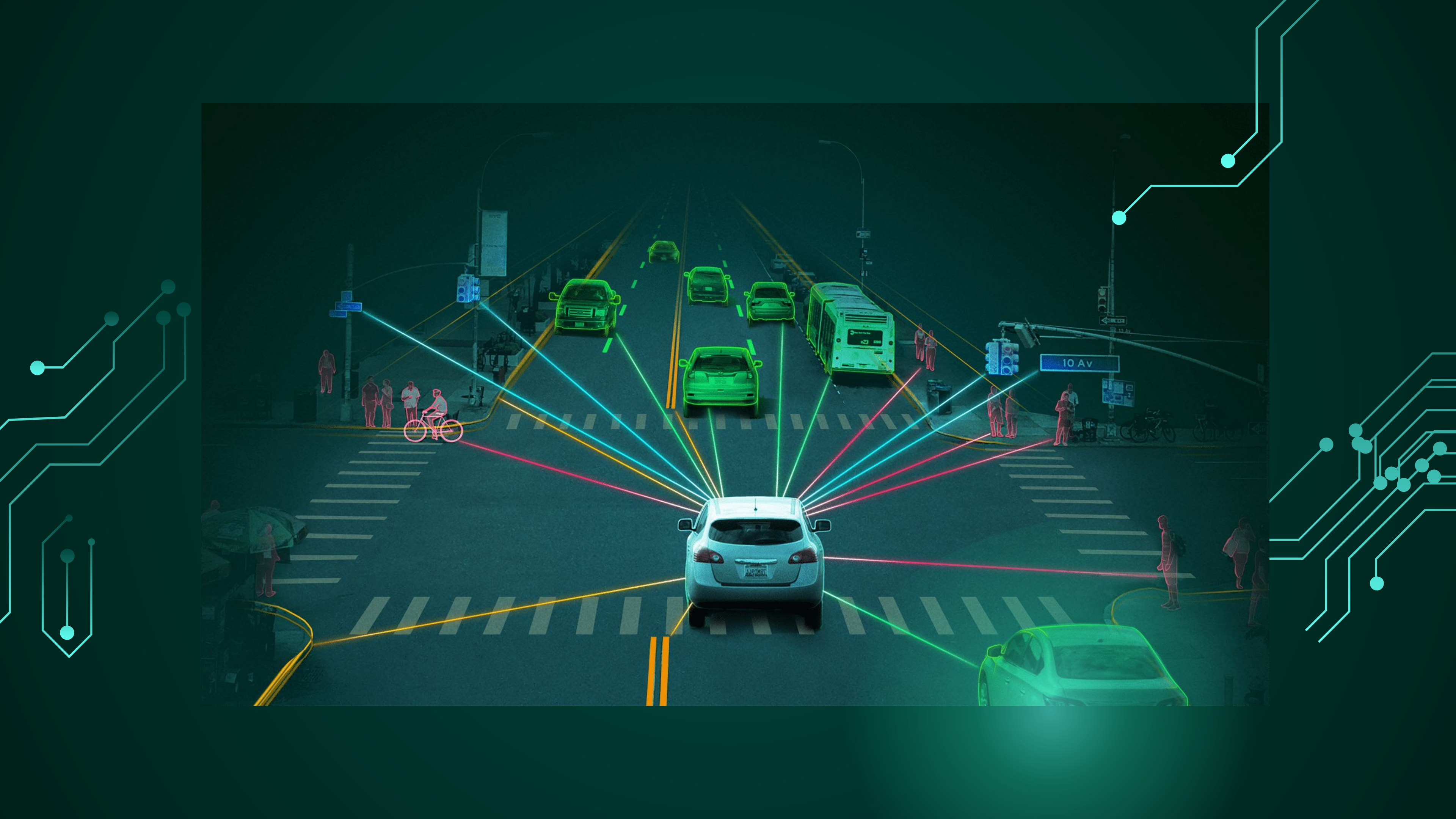
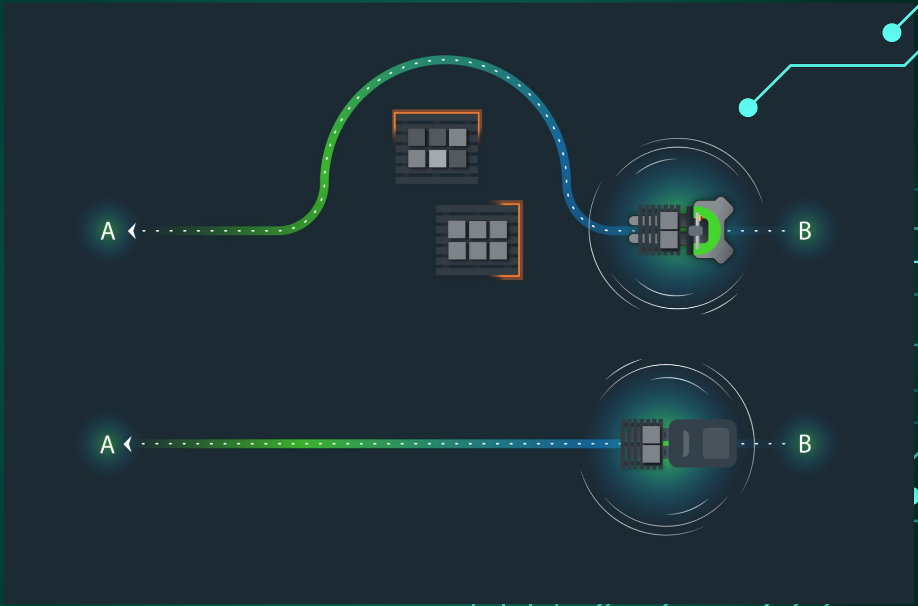
INTRODUCTION


10 Av

Need

- Optimal Paths: Choose the best routes considering distance, obstacles, and terrain for quicker and energy-efficient travel
- Collision-Free Navigation: Employ strategies to avoid collisions with static and moving obstacles, ensuring safe robot movement.
- Dynamic Adaptation: Adapt paths in real time to changing conditions like new obstacles or terrain variations for uninterrupted navigation.
- Scalable Planning: Design systems capable of managing complexity and scaling up for efficient navigation in diverse environments.



Path Planning Techniques in Robotics

Grid-Based Algorithms

Dijkstra's Algorithm
A* Algorithm

Sampling-Based Algorithms

Probabilistic Roadmap (PRM)
Rapidly Exploring Random Tree (RRT)

Potential Field Methods

Artificial Potential Field
Vector Field Histogram (VFH)

Optimization-Based Techniques

Linear Programming
Quadratic Programming

Machine Learning-Based Approaches

Deep Reinforcement Learning (DRL)
Neural Network-Based Models

Hybrid Methods

Potential Field + A*
Sampling-Based + Optimization

Our Attempt

- To enhance robotics motion planning by combining traditional sampling-based algorithms with deep learning techniques.

- Using PyTorch for deep learning.
- Combining of RRT* and Motion Planning Networks (MPNet).

- Implementation: PyTorch for algorithms.

- Training neural networks with refinement through RRT* Algorithm provided ground truth values, using NN architecture for improved time complexity and decision-making in path planning.

- Faster collision-free path finding, generalization to new environments, suitability for real-time robotics applications, overcoming computational challenges.

02

Formulation

Workflow

- Split map data into nodes: Start & Goal.
- Known Maps for training, Unknown Maps for testing.
- Feed Maps into RRT algorithm for path generation.
- Encode Known Maps for training.
- Train neural network model to learn map-path mapping.
- During testing, use trained model to predict path steps iteratively.
- Simulate the outcomes into a virtual environment.
- Implement into real world scenario (Static / Dynamic) using appropriate hardware.

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Methods

```
τa ← {xstart}
τb ← {xgoal}
τ ← Ø
Reached ← False
for i ← 0 to N do
    xnew ← Pnet(Z, τa(end), τb(end))
    τa ← τa ∪ {xnew}
    Connect ← steerTo(τa(end), τb(end))
    if Connect then
        τ ← concatenate(τa, τb)
        return τ
return Ø
```

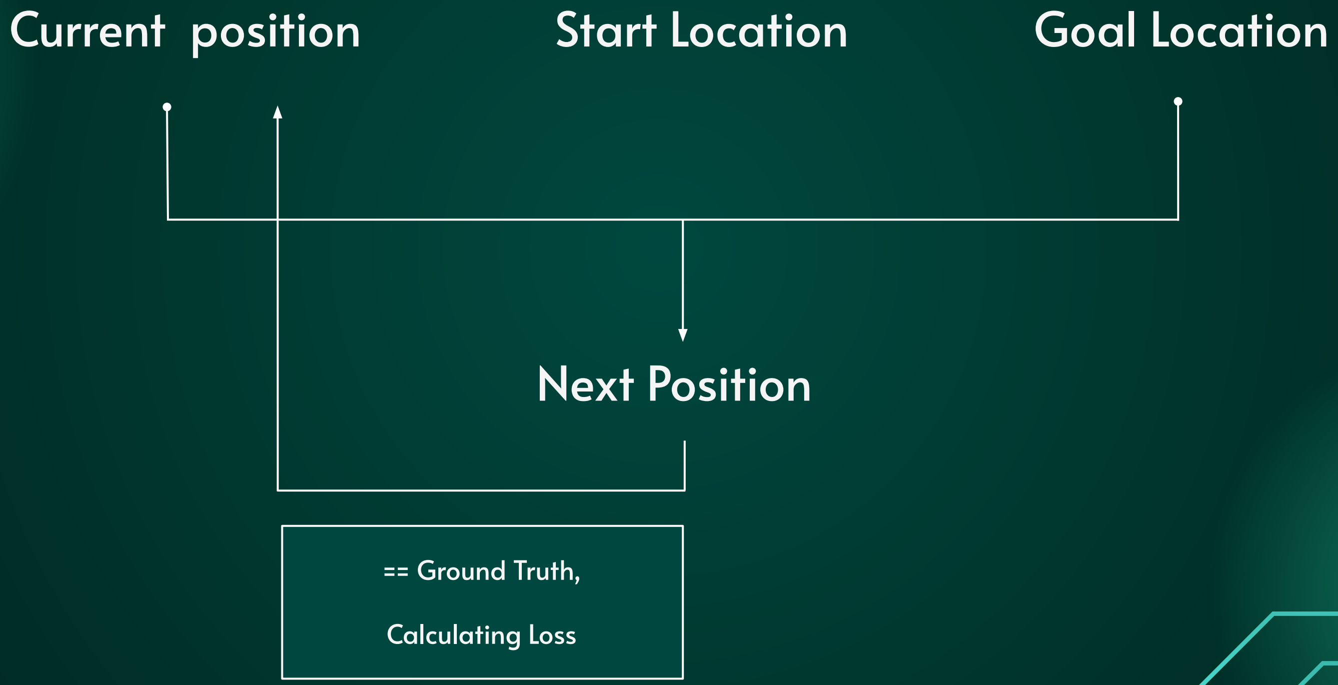
Planner Pseudocode

Contractive Auto-Encoder (C A E)

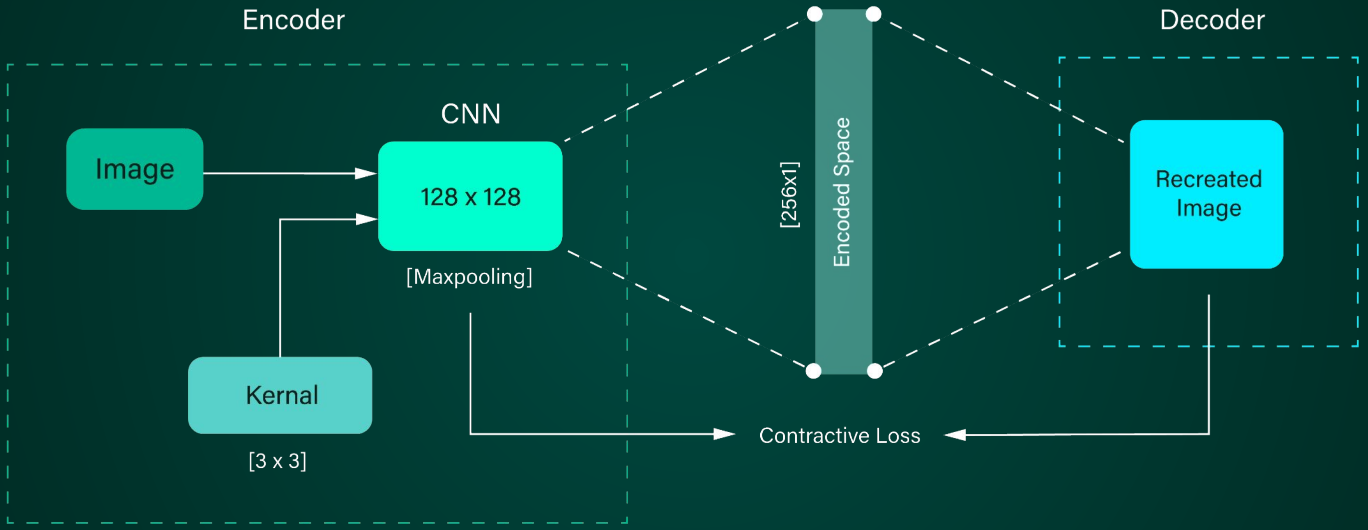
Encoder **Decoder**

MSE + Contractive Loss

Neural Planner



CAE


Encoder
Decoder
CNN
Image
128 x 128
[Maxpooling]
Kernal
[3 x 3]
[256x1]
Encoded Space
Recreated Image
Contractive Loss

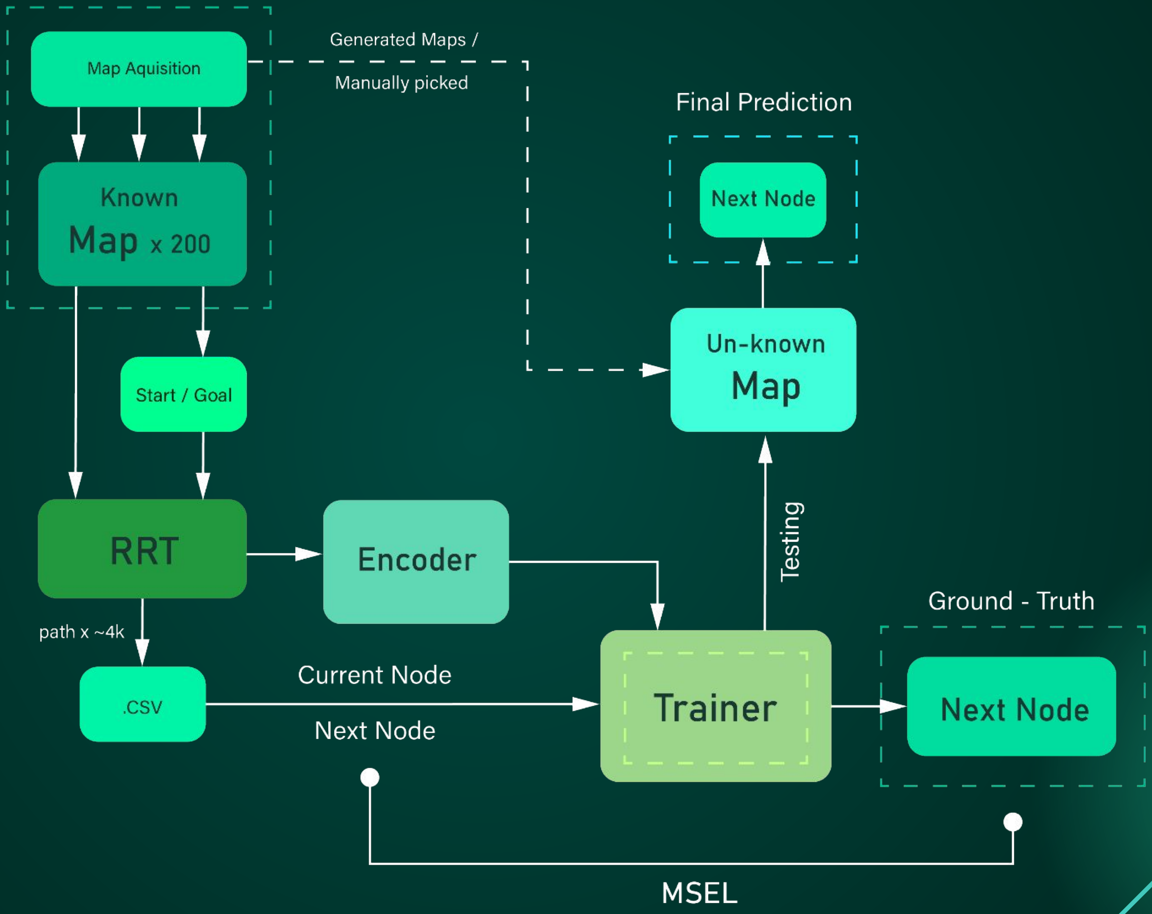
Generating Datasets

```
8,27
5,103,133940,247324,99
6.760649125548583,93.78668133543
9.325648428521857,89.49473788569227
9.922695775612356,84.53051242089596
10.33290345073481,79.54736786516906
14.932405211368259,77.58660690219327
19.89464279600004,78.19995684608156
24.201950782035123,75.66084323825729
28.125599070256943,72.56165235831233
31.837996827652834,69.21230870755298
36.62655005158725,70.6509740687636
38.38246550844562,65.96944003509837
41.4977366119822,62.05854679295151
36.731221913498395,60.548468109856536
33.66383057615008,56.599910096662285
```

200 Randomized maps

40000 Paths

Overview

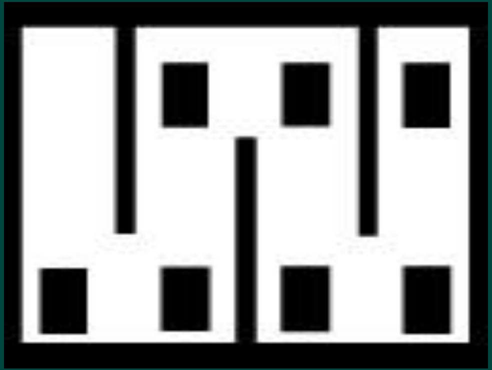

Map Aquisition
Generated Maps /
Manually picked
Final Prediction
Next Node
Known
Map x 200
Un-known
Map
Start / Goal
RRT
Encoder
Testing
Ground - Truth
path x ~4k
Current Node
.CSV
Trainer
Next Node
Next Node
MSEL

04

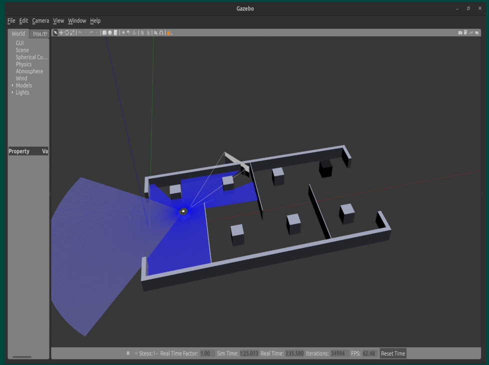
Simulation

ROS

```python
# Define the action set
action_set = [(0, RPM1), (RPM1, 0), (RPM1, RPM1), (0, RPM2), (RPM2, 0), (RPM2, RPM2), (RPM1, RPM2), (RPM2, RPM1)]
```



128*128 Map



Gazebo Classic

Turtlebot3 @RAL

05

Implementation & Challenges

Challenges

- RRT data generator being stuck at different intervals.
- Varying dimensions of encoder output disrupting matrix multiplication.
- Oversized dimensions (128*128) of dataset.
- Data collected not meeting the required format for training the network.

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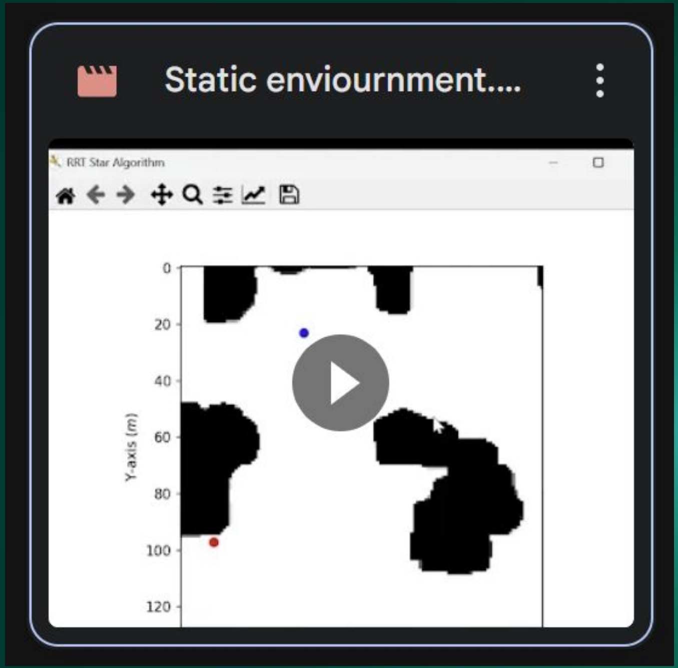
Outcomes



Immobilized obstacles in the same environment

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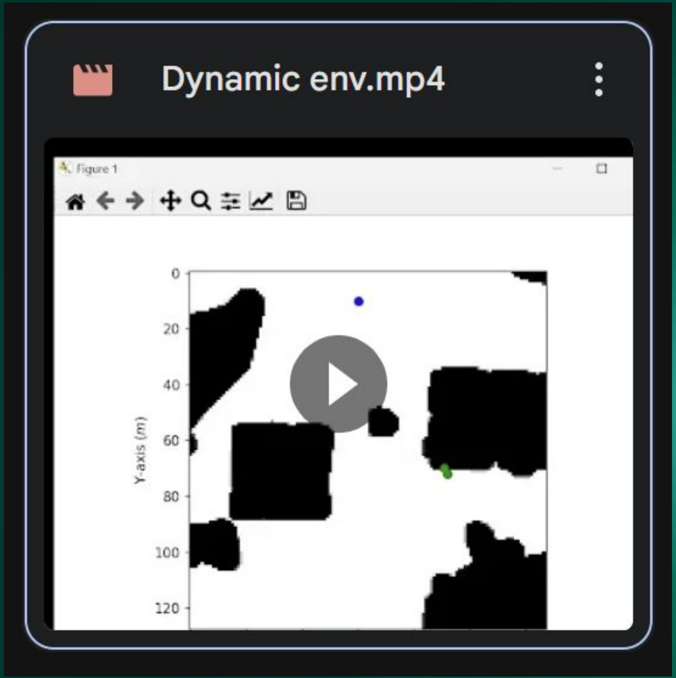

Mobilized obstacles in varying environments

Click on text

RESOURCES

- **Research papers referred:**
- 1) *Motion Planning Networks:* / https://arxiv.org/abs/1806.05767
- 2) *Deep RRT*:* / https://ojs.aaai.org/index.php/SOCS/article/view/21803

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DOES ANYONE HAVE ANY QUESTIONS?