Design of an Autonomous Robot for Indoor Navigation using A* Search and Dynamic Environment Sensing

*Course Project: CSE440 - Artificial Intelligence

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Abstract—Indoor autonomous navigation represents a critical challenge in modern robotics, requiring systems that can calculate optimal paths while reacting to unforeseen obstacles. This project details the design and implementation of a navigation stack for an autonomous robot, centered around the A* (A-Star) search algorithm. The system is designed to operate in a grid-based environment where sensor data is dynamically updated to reflect real-world constraints.

We developed a robust simulation engine using Python to validate our path planning logic. The core algorithm utilizes a Euclidean Heuristic to enable 8-way omnidirectional movement, allowing the robot to traverse diagonals for trajectory optimization. The system features a real-time visualization interface that simulates sensor inputs (via dynamic obstacle drawing) and visualizes the "Frontier Exploration" phase of the algorithm. This report documents the system architecture, the mathematical derivation of the cost functions, the software implementation challenges, and the experimental results demonstrating the robot's ability to navigate complex "U-Turn" traps and mazes efficiently.

Index Terms—Autonomous Navigation, A* Algorithm, Path Planning, Robotics, Dynamic Sensing, Grid Search, Heuristics.

I. Introduction

THE development of autonomous mobile robots (AMRs) has transitioned from academic curiosity to industrial necessity. From automated guided vehicles (AGVs) in Amazon warehouses to disinfection robots in hospitals, the core requirement remains the same: the ability to move from Point A to Point B safely and efficiently.

Navigation in indoor environments presents unique challenges compared to outdoor GPS-based navigation. Indoor environments are structured but dynamic; furniture moves, doors open and close, and humans walk through the robot's path. Therefore, a pre-computed map is rarely sufficient. An effective robot must possess a "Global Planner" that can recalculate routes in real-time as its sensors update its internal knowledge of the environment.

A. Project Motivation

In our CSE440 Artificial Intelligence course, we studied various search strategies. While algorithms like Dijkstra ensure the shortest path, they are computationally expensive for large maps. Greedy Best-First Search is fast but not optimal. The A* algorithm strikes a balance by using a heuristic to guide the search.

Our group aimed to design a navigation system that bridges the gap between theoretical algorithm design and practical robotic implementation. We wanted to answer specific engineering questions: How does the choice of heuristic affect the robot's turning radius? How can we simulate dynamic obstacles (like a sudden wall appearing) without building a physical prototype?

B. Objectives

The primary objectives of this project were:

1) Navigation Logic: To implement a custom A* engine capable of 8-way movement (Moore Neighborhood) to approximate a differential drive robot's kinematics.
2) Dynamic Environment Simulation: To build a GUI where "sensor readings" (obstacles) can be added

dynamically, forcing the user to evaluate the algorithm's adaptability.

3) Visualization: To deconstruct the "black box" of AI by visualizing the Explored Set (the robot's thought process) versus the Optimal Path (the execution).

II. Theoretical Framework

The backbone of our robot's decision-making process is the A* Search Algorithm. To ensure our implementation was robust, we first established the mathematical foundation.

A. The Cost Function

The robot makes decisions based on minimizing the total estimated cost, $f(n)$, for every node n in the grid:

$$f(n) = g(n) + h(n) \tag{1}$$

Where:

- $g(n)$: The cost to travel from the Start Node to node n.
- $h(n)$: The heuristic estimate of the cost from node n to the Goal Node.

B. Grid Topology and Kinematics

We modeled the indoor environment as a discrete occupancy grid. A critical design decision was determining the connectivity of this grid.

- 4-Way Connectivity (Von Neumann): The robot can only move North, South, East, West. This results in "Manhattan" paths, which are unnatural for real robots.
- 8-Way Connectivity (Moore): The robot can also move diagonally (NE, NW, SE, SW).

We selected the 8-Way model to allow for smoother trajectories. However, this introduces a cost variation.

- Straight Move Cost: 1.0
- Diagonal Move Cost: $\sqrt{2} \approx 1.414$

It was vital to implement this $\sqrt{2}$ cost in our code. If diagonal moves were treated as cost 1, the robot would prefer zig-zagging, which is inefficient.

C. Heuristic Selection: The Euclidean Metric

For A* to be optimal, the heuristic $h(n)$ must be admissible (never overestimate the cost).

1) Why we rejected Manhattan Distance: The Manhattan distance is defined as:

$$h(n) = |x_{start} - x_{goal}| + |y_{start} - y_{goal}| \tag{2}$$

In an 8-way grid, this is inadmissible. Consider a move from $(0, 0)$ to $(1, 1)$. The actual cost is $\sqrt{2} \approx 1.41$. The Manhattan estimate is $1 + 1 = 2$. Since $2 > 1.41$, the heuristic overestimates, potentially causing the robot to miss the best path.

2) Adoption of Euclidean Distance: We chose the Euclidean distance:

$$h(n) = \sqrt{(x_{start} - x_{goal})^2 + (y_{start} - y_{goal})^2} \tag{3}$$

This represents the straight-line distance "as the crow flies." Since no path on a grid can be shorter than a straight line, this heuristic is guaranteed to be admissible, ensuring our robot always plans the shortest possible path.

III. System Architecture

Our autonomous navigation system is divided into two primary software modules: the Planner Backend and the Simulation Frontend.

A. The Planner Backend (astar_logic.py)

This module serves as the "brain" of the robot. It is a pure logic implementation independent of the visualization.

- Input: A binary occupancy grid (0=Free, 1=Obstacle), Start coordinates, Goal coordinates.
- Data Structures:
  - Open Set: A Min-Heap (Priority Queue) to efficiently retrieve the node with the lowest f score.
  - Closed Set: A Hash Set to track visited nodes and prevent cycles.
- Output: The sequence of coordinates representing the path.

B. The Simulation Frontend (main.py)

This module acts as the "environment" and "sensor interface."

- Sensor Simulation: We utilized a "Brush" tool in the GUI. When a user draws on the grid, they are effectively simulating Lidar sensors detecting a wall. The robot's map is updated in real-time.
- Visualization Stack: We used matplotlib.animation to render the robot's state. We separated the visualization into two phases:
  1) Exploration Phase: Visualizing the explored_nodes to show how the robot "searches" the space.
  2) Execution Phase: Moving the robot marker along the calculated path.

IV. Implementation Details

This section details the engineering challenges we faced during the coding phase and the solutions we devised.

A. Efficient Priority Queue Management

In a 100×100 grid, there are 10,000 possible nodes. A standard list sorting approach would have a time complexity of $O(N \log N)$ per step, which is too slow for real-time robotics. We utilized Python's heapq module to implement a binary heap. This allows us to push and pop nodes with $O(\log N)$ complexity.

```python
# From astar_logic.py
while oheap:
    current = heapq.heappop(oheap)[1]

    # Track for visualization
    explored_nodes.append(current)

    if current == goal:
        # Reconstruct path logic...
        return path, explored_nodes
```

Listing 1. Heap Management in A* Logic

B. Dynamic Environment Modeling

A key feature of our robot is the ability to handle dynamic updates. We achieved this by treating the grid as a mutable NumPy array. The MazeApp class in main.py listens for mouse events. When a drag event is detected, we slice the array and update the values.

```python
# Simulating obstacle detection via UI
def on_motion(self, event):
    if self.drawing:
        c, r = int(event.xdata), int(event.ydata)
        # Apply brush radius
        self.grid[r-rad:r+rad, c-rad:c+rad] = 1
        self.img.set_data(self.grid)
```

Listing 2. Sensor Simulation (Drawing)

By using set_data instead of redrawing the entire plot, we maintained a high frame rate, essential for simulating a responsive robot.

C. Handling Diagonal Cost

We explicitly coded the cost logic to differentiate between straight and diagonal movements.

```python
# i, j are coordinate offsets
move_cost = np.sqrt(i**2 + j**2)
tentative_g_score = g_score[current] + move_cost
```

This simple line of code ensures that the robot prefers a path of 10 straight steps (Cost=10) over a path of 8 diagonal steps (Cost ≈ 11.3), enforcing energy efficiency.

V. Experimental Results

We validated our robot's navigation logic across three distinct environmental topologies.

A. Scenario A: Open Field (Baseline)

Setup: An empty 100×100 grid. Start at $(2, 2)$, Goal at $(97, 97)$. Result: The robot successfully calculated a straight diagonal line. Analysis: The "Exploration Phase" visualization showed a narrow beam of explored nodes directly connecting start to goal. This confirms the Euclidean heuristic is efficiently pruning the search space. A generic Dijkstra implementation would have explored the entire grid in a circular pattern, wasting computational resources.

B. Scenario B: The "U-Turn" Trap

Setup: We drew a large U-shaped wall between the start and goal. This is a classic "Local Minima" trap for greedy robots. Result: The robot entered the U-shape, realized the path cost ($g(n)$) was increasing without getting closer to the goal, and correctly backtracked to navigate around the wall. Analysis: This demonstrated the robustness of A*. A purely Greedy Best-First Search often gets stuck in such traps because it blindly follows the heuristic $h(n)$. By including the path cost $g(n)$, our robot avoided the trap.

C. Scenario C: The Maze (Complex Indoor Environment)

Setup: A complex layout simulating rooms and corridors. Result: The robot found the optimal path through the corridors. Analysis: In narrow corridors, the heuristic becomes less effective because the robot cannot move in a straight line. We observed the exploration visualization "filling up" dead ends completely before abandoning them, which is the expected behavior of an optimal planner.

VI. Design Challenges and Solutions

Developing this autonomous system was not without hurdles. We encountered specific engineering issues that required iterative debugging.

A. The Coordinate System Mismatch

A major point of confusion during the initial integration was the discrepancy between the Matrix Coordinate System (used by numpy and our logic) and the Cartesian Coordinate System (used by matplotlib for visualization).

- Matrix: '(row, col)' where '(0,0)' is top-left.
- Cartesian: '(x, y)' where '(0,0)' is usually bottom-left.

Initially, our robot would detect an obstacle at 'x=10' but update the grid at 'row=10', effectively rotating the map by 90 degrees. We solved this by strictly enforcing a '(row, col)' convention in the backend and only swapping to '(x, y)' at the exact moment of rendering in main.py.

B. Visualization Latency

When simulating large maps, attempting to plot the "Explored Nodes" one by one caused the simulation to lag significantly. We optimized this by batching the visualization. Instead of: plot(point) (10,000 calls) We used: set_offsets(array_of_points) (1 call per frame) This optimization reduced the rendering time by over 90%, allowing for smooth real-time performance.

VII. Discussion

The results indicate that our A* implementation is suitable for the global planning layer of an autonomous indoor robot. The modular design allows the logic to be decoupled from the simulation; theoretically, the astar_logic.py file could be uploaded to a Raspberry Pi controlling a physical robot, provided the sensor data is formatted into a binary grid.

One limitation we observed is the "jagged" nature of grid-based paths. While mathematically optimal on a grid, a physical robot cannot make instant 45-degree turns without stopping. A "Local Planner" (like DWA or TEB) would be required to smooth these corners into kinematic trajectories.

VIII. Conclusion

This project successfully demonstrates the design of a navigation system for an autonomous robot. By integrating the A* algorithm with a dynamic environment simulator, we created a platform that validates path planning strategies in real-time.

We met our objectives of implementing 8-way movement, validating the Euclidean heuristic, and visualizing the decision-making process. The system robustly handles obstacles and calculates optimal paths even in deceptive "trap" scenarios. This work serves as a foundational step toward building a fully physical autonomous mobile robot.

IX. Future Work

To further enhance the autonomy of the system, we propose:

1) Path Smoothing: Implementing post-processing algorithms like B-Splines to generate smooth curves for differential drive motors.
2) Weighted Terrain: Instead of binary (Wall/Free), implementing variable costs (e.g., Carpet=1.0, Tile=0.8) to simulate different floor types.
3) D* Lite Integration: Implementing dynamic replanning algorithms that can handle moving obstacles (like walking humans) more efficiently than re-running A*.

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