



Project Documentation

Contents

1. Introduction
2. Problem Definition
3. Genetic Algorithm Implementation
4. Results, Analysis and Appendix
5. Conclusion

Introduction

Navigating environments with obstacles and constraints is a crucial challenge in robotics applications. Finding optimal paths for robots to move efficiently and safely requires robust algorithms that can handle diverse scenarios. This document presents a genetic algorithm (GA) approach to address this challenge.

Problem Definition:

Input:

- Environment Map: Represented as a grid with obstacles, where each cell can be either occupied or free.
- Start and Goal Positions: Initial and final positions where the robot starts and needs to reach.

Output:

- Optimal Path: A sequence of movements or actions that the robot can take to reach the goal while avoiding obstacles and following the constraints.

Challenges:

- Obstacle Avoidance: The robot needs to navigate around obstacles to reach the goal.
- Optimization: Finding the shortest or most efficient path based on defined criteria (e.g., distance traveled, time taken).
- Constraint Adherence: Ensuring that the robot respects limitations such as speed, turning capabilities, or any other imposed restrictions.
- Real-time Planning: For dynamic environments, the path planning might need to be adaptable and quick.

Genetic Algorithm Implementation :

Individual Class:

- **Description:** Represents an individual path as a sequence of movements for the robot within the environment
- **Attributes:**
 - **genes:** Represents the sequence of moves as a list of tuples (e.g., (1, 0) for moving right, (0, -1) for moving down).
- **Methods:**
 - **__init__(self, genes=None):** Initializes an individual with provided genes or an empty list if not specified.

Obstacle Class:

- **Description:** Defines obstacles within the environment by specifying their position and dimensions.
- **Attributes:**
 - **x:** x-coordinate of the obstacle's position.
 - **y:** y-coordinate of the obstacle's position.
 - **width:** Width of the obstacle.
 - **height:** Height of the obstacle.
- **Methods:**
 - **__init__(self, x, y, width, height):** Initializes an obstacle with specified position and dimension

Graph Class:

- **Description:** Represents the environment in which the robot operates, including dimensions, start and end points, and randomly generated obstacles.
- **Attributes:**
 - **width:** Width of the environment.
 - **height:** Height of the environment.
 - **start:** Starting point for the robot's path.
 - **end:** Ending goal point for the robot's path.
 - **obstacles:** List of obstacles within the environment.

➤ **Methods:**

- `generate_random_obstacles(self, num_obstacles)`: Generates a specified number of random obstacles within the environment.
- `is_valid_move(self, x, y)`: Checks if a given move is valid, considering obstacles and boundaries.

GeneticAlgorithm Class:

➤ **Description:** Implements the genetic algorithm for robot path planning within the defined environment.

➤ **Attributes:**

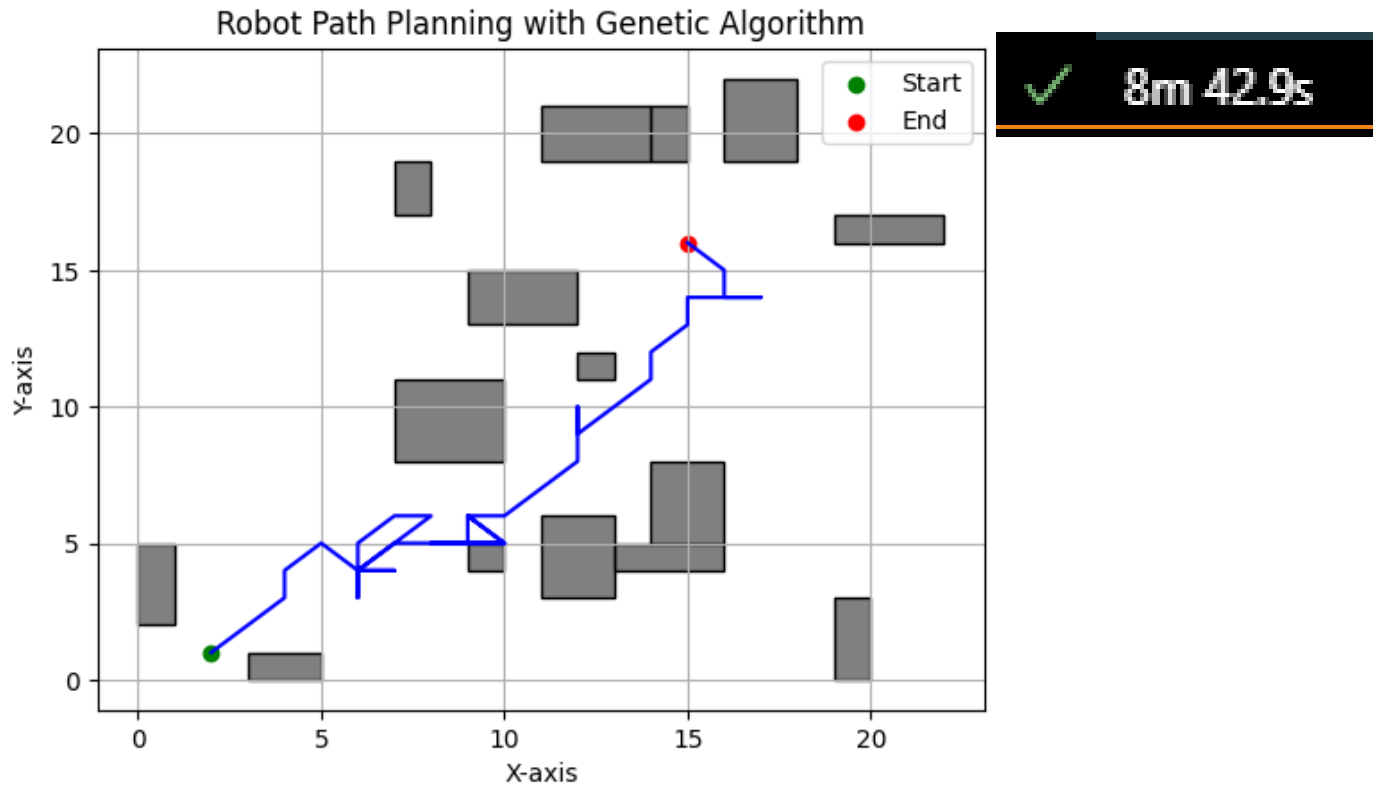
- `population_size`: Size of the population for genetic algorithm operations.
- `graph`: The environment represented as a graph.
- `start`: Starting point for the robot's path.
- `end`: Ending goal point for the robot's path.
- `iterations`: Number of iterations for the genetic algorithm.
- `population`: List representing the current population of individuals (possible paths).

➤ **Methods:**

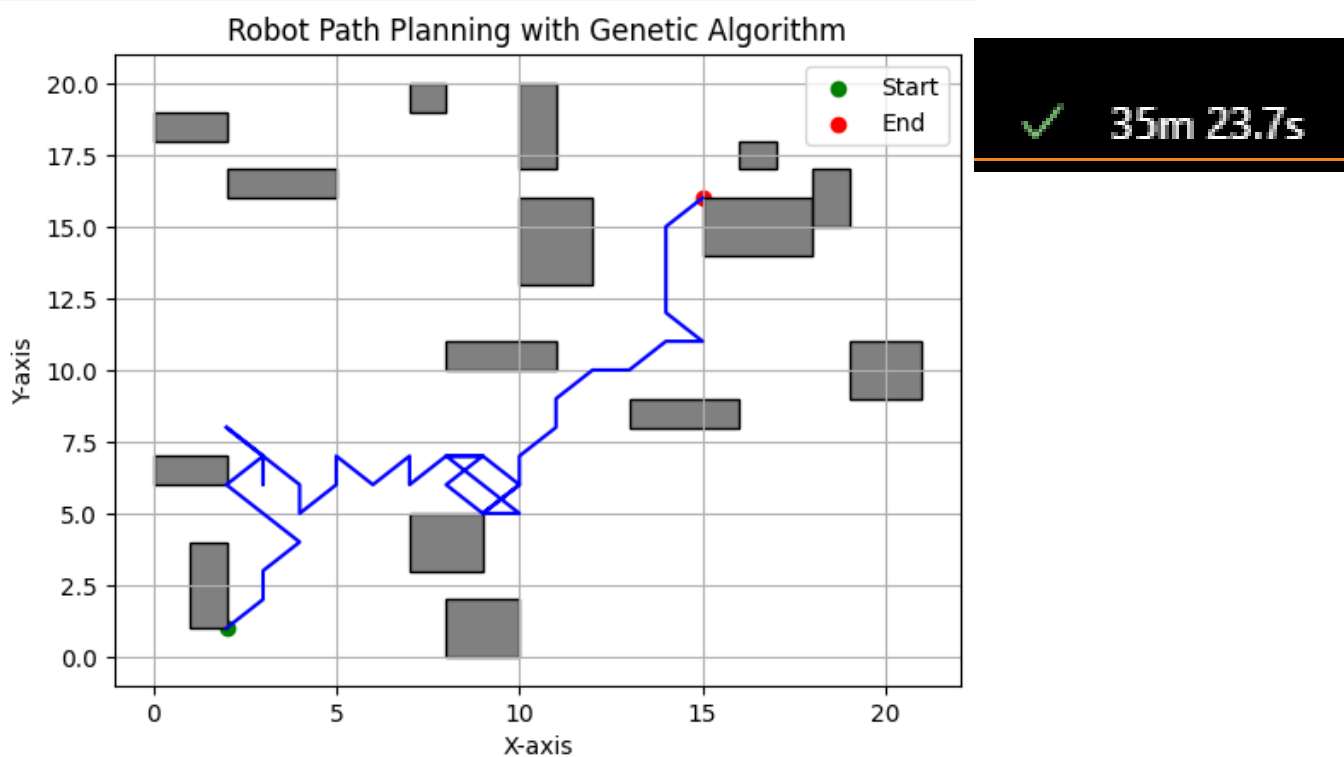
- `generate_random_individual(self)`: Generates a random individual (path) for the population.
- `initialize_population(self)`: Initializes the population with random individuals.
- `fitness_function(self, individual)`: Evaluates the fitness of an individual path.
- `select_parents(self)`: Selects individuals from the population for reproduction based on fitness.
- `crossover(self, parent1, parent2)`: Performs crossover operation to create offspring from parents.
- `mutate(self, individual)`: Introduces random changes to an individual's path while ensuring validity.
- `evolve(self)`: Drives the evolution process of the population through multiple iterations.
- `plot_solution(self, best_individual)`: Visualizes the best path found by the genetic algorithm.

Results, Analysis and Appendix:

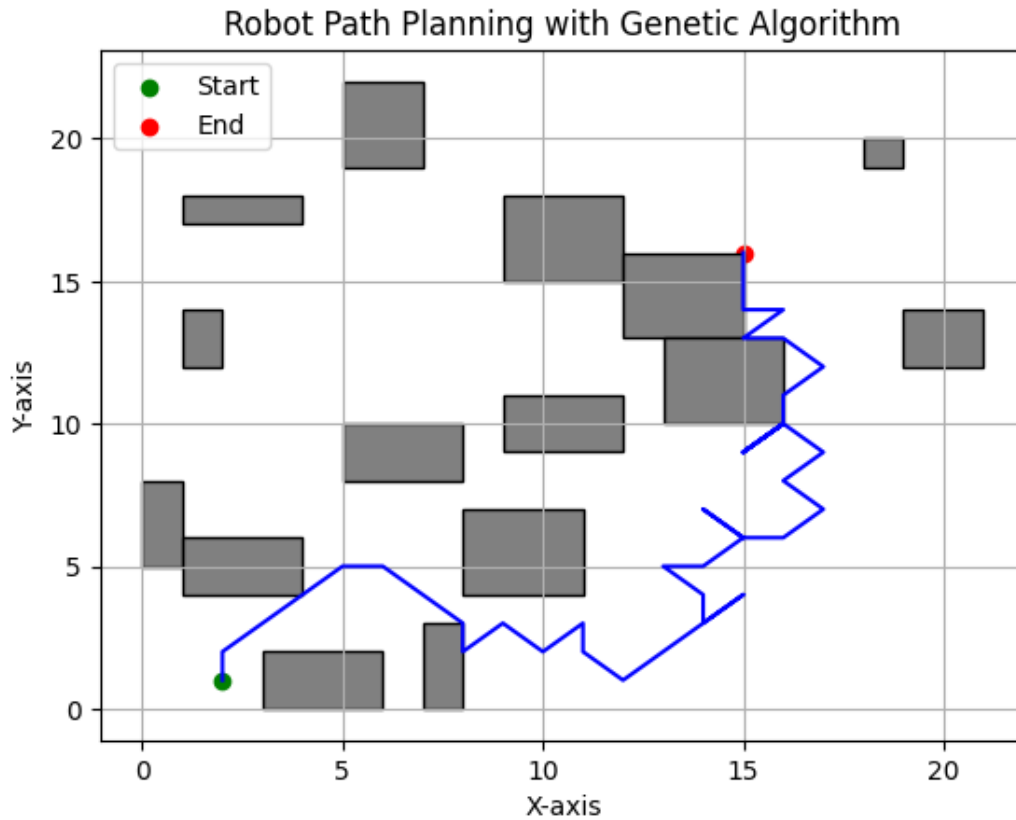
population size	100	iterations	500
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population size	600	iterations	50
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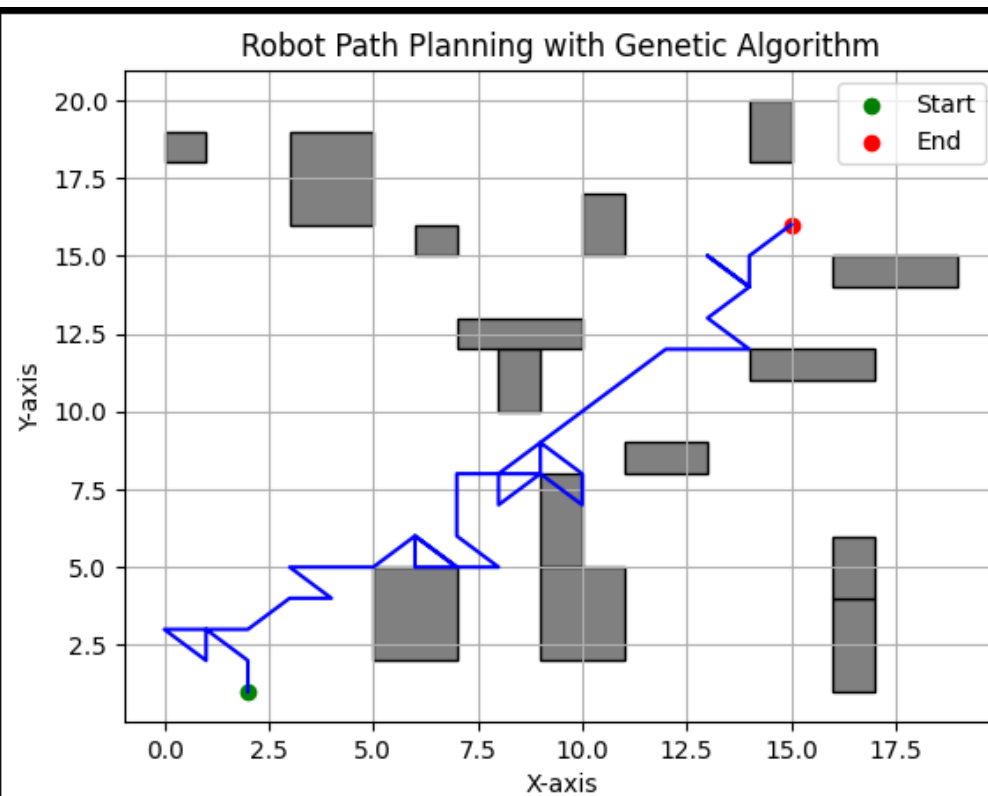


population size	100	iterations	5000
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✓ 109m 11.4s

population size	50	iterations	200
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✓ 1m 4.3s

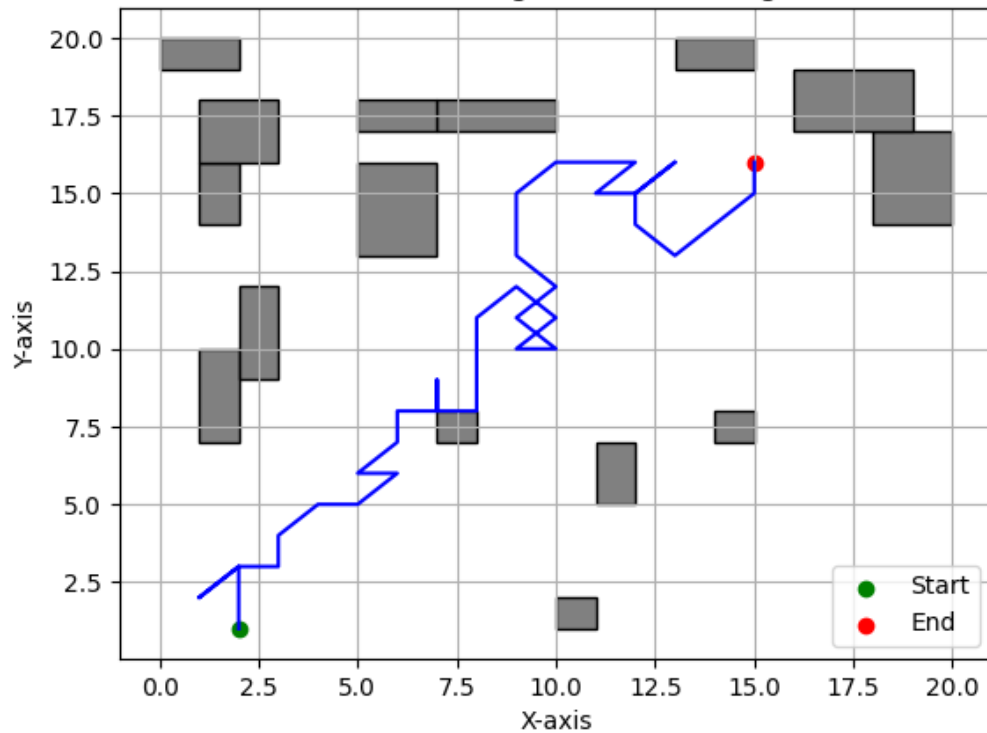
population size

50

iterations

500

Robot Path Planning with Genetic Algorithm



2m 53.2s

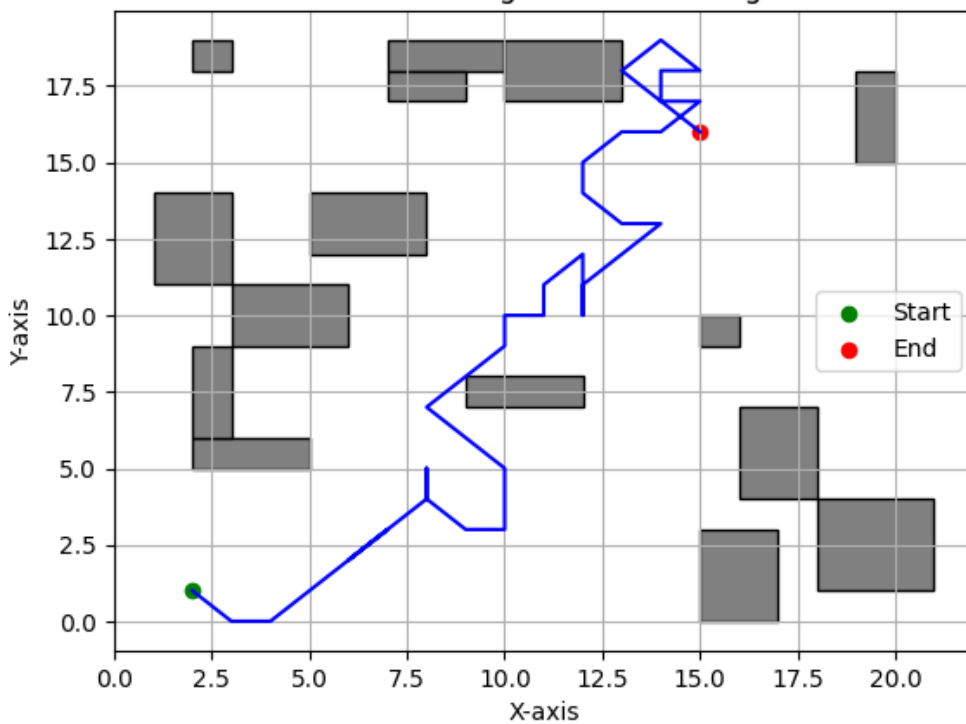
population size

30

iterations

5000

Robot Path Planning with Genetic Algorithm



14m 23.5s

conclusion:

The application of genetic algorithms to tackle robot path planning in obstacle-laden environments manifests as a promising avenue in robotics. Key insights gleaned from this approach include:

- **Algorithmic Efficacy:** Genetic algorithms offer a systematic and efficient means to navigate complex environments while finding optimal paths.
- **Class Structures' Harmony:** The synergy among Individual, Obstacle, Graph, and GeneticAlgorithm classes fosters a cohesive environment for simulating and determining optimal robot paths.
- **Flexibility and Adaptability:** This approach accommodates various environmental configurations and constraints, displaying adaptability in dynamically changing scenarios.

In essence, leveraging genetic algorithms in robot path planning furnishes a robust methodology that empowers robots to navigate intricate environments adeptly, fostering efficiency and safety in their operations.

