
An Experiment on Robotic Navigation and Object Manipulation Tasks in Simulated Room Environment

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Abstract

This report documents the default coursework project for CS5478, completed by a group of three students. The project focuses on implementing navigation and object manipulation tasks for a mobile robot within a simulation environment based on the Pybullet framework. The primary objective of the navigation task is to move the robot from a start position to a predefined goal while avoiding obstacles. A* algorithm is employed for path planning, incorporated with customized motion control functions. This enhanced solution significantly improves path-finding speed and stability, especially in scenarios with narrow passages. The manipulation task requires the robot to pick up and place a mug with its arm. The procedure for grasping and placing the mug is deterministic, based on the predefined environment and robot arm configurations, ensuring task execution is precise and efficient. The code is available in the GitHub repository: <https://github.com/GeorgeZXY/CS5478Project>. Demo videos are uploaded at https://drive.google.com/drive/folders/1BTEPZ8hFLefzQSI_LjKZaurF8oTKmUQq?usp=sharing

1 Introduction

Robotics has become a promising area of study in recent years. Robots could offer solutions to a wide range of applications, from autonomous driving to automation of household chores. Two fundamental aspects in robotics are navigation, where robots move efficiently through a space, and manipulation, which involves interacting with objects to perform specific tasks. These capabilities are essential for robots to be functional and useful in various scenarios and environments.

As part of the coursework for CS5478 Intelligent Robots: Algorithms and Systems in academic year 24/25, this project explores the implementation of navigation and manipulation tasks using a mobile robot in a simulated environment. The navigation task involves moving the robot from a start position to a goal while avoiding obstacles, requiring efficient path-planning techniques. After reaching the goal area, it needs to perform a manipulation task using the multi-linkage arm and gripper to pick up a mug and place it in a drawer. The drawer is initialized with a fixed position while the mug is placed randomly within an small area that is on top of the drawer.

The project adopts a structured approach by leveraging predefined locations and utility functions for object localization and robot actions, simplifying the challenges within the controlled simulation environment. The navigation is achieved by path planning using A* algorithm from obstacle locations based on the environment. The pick and place of the mug is performed using a fixed procedure with parameters locating the mug object.

This report presents methods applied to implement the specified tasks, followed by analysis on the results, with discussion of challenges encountered and possible improvements for future works.

35 2 Related Works

36 Recent advancements in robotics have enabled significant progress in the domains of manipulation,
37 navigation, and sensor integration. Several studies have explored path planning techniques for
38 autonomous robots in dynamic environments, where real-time obstacle detection and avoidance are
39 critical. In [1], the authors propose a framework for real-time path planning based on LiDAR data,
40 enabling robots to detect and avoid obstacles dynamically while maintaining a feasible trajectory.
41 Similarly, [2] integrates vision and LiDAR data for simultaneous localization and mapping (SLAM),
42 enhancing the robot’s ability to navigate complex, unstructured environments.

43 In the area of manipulation, much work has been done to improve the grasping and manipulation
44 of objects in both simulated and real environments. [3] describes an advanced grasping technique
45 using force and vision feedback to adjust the gripper’s motion and apply appropriate forces to
46 maintain an object’s stability. Another method focuses on inverse kinematics and trajectory planning
47 to improve robotic arm control for pick-and-place tasks [4]. In their approach, [5] use machine
48 learning techniques to predict the optimal trajectories for robotic arms based on sensor feedback and
49 task-specific goals. However, as seen in the current implementation, limitations arise from simplified
50 simulation models, especially with regard to object grasping and physical interaction modeling. For
51 instance, the reliance on constraint-based methods, such as those implemented in [6], results in
52 non-realistic behaviors that fail to capture nuanced aspects of contact forces and friction in robotic
53 interactions.

54 Moreover, several studies have investigated the integration of vision-based systems for object detection
55 and task planning in robots. In [7], a top-down camera view is employed to assist a robotic arm
56 in picking objects from a cluttered environment. This approach allows the robot to estimate the
57 position of objects and plan its motion accordingly. Vision-based systems have also been shown to
58 be effective in dynamic environments, with [8] demonstrating the use of vision-based feedback to
59 adapt to moving obstacles in real-time path planning. However, limitations exist when incorporating
60 vision with inverse kinematics and trajectory planning, as noted in [9], where the lack of accurate
61 3D understanding can hinder the robot’s ability to complete tasks such as pick-and-place with high
62 precision.

63 These works highlight key challenges in robotics, such as ensuring reliable object manipulation,
64 improving dynamic path planning, and leveraging vision systems effectively. Our approach, similar
65 to existing frameworks, aims to enhance robot autonomy by integrating these capabilities, with a
66 focus on improving the accuracy and realism of grasping techniques, as well as refining path planning
67 methods for dynamic and unstructured environments.

68 3 Methodology

69 3.1 Setup

70 This project is conducted in a Pybullet simulation environment. The environment setup is provided
71 from course material. This environment mimics an simplified household setting with multiple rooms,
72 such as bedroom, living room and kitchen. Various objects like bed, drawer, fridge etc. are placed
73 in the rooms. The robot used is a mobile robot with an robotic arm attached to it. The robot’s base
74 provides mobility on the floor with forward, backward and turning functionalities. The robotic arm’s
75 first link is a long vertical link with translational joint to adjust height. Second link is a horizontal
76 link with translational joint to perform stretch. This stretch direction is perpendicular to the base’s
77 forward motion direction. The end effector is a 2-finger gripper and is mounted on 2 rotational links
78 that serve for roll and pitch. The task involves 2 parts. First, the robot is initialized in the kitchen and
79 it should navigate to the bedroom and reach goal position beside bed and in front of drawer. Second,
80 the robot would pick up a mug that is placed on the drawer and put it in an open cabinet of the drawer.

81 3.2 Navigation

82 By integrating real-time obstacle detection (through simulated data), efficient path planning (using
83 the A* algorithm on a grid-based map), and precise robot control (via a PID controller for motion
84 execution), the system ensures that the robot can reach its goal safely and efficiently. The system takes

85 into account the physical dimensions of the robot, avoiding collisions by adhering to inflated obstacle
86 boundaries, and dynamically adjusts the path based on the changing environmental conditions.

87 3.3 Real-time Obstacle Detection Using Sensor Data

88 3.3.1 Setting Up the Simulation Environment with PyBullet

89 The simulation environment is initialized using PyBullet, a physics engine that enables realistic inter-
90 action between the robot and objects in the environment. The `init_scene` function in `stretch.py`
91 sets up the environment by loading various objects, such as tables, walls, cabinets, and bottles. Each
92 object is assigned a unique identifier (`object_id`), which is crucial for tracking and managing these
93 objects within the simulation.

94 3.3.2 Obtaining Object Bounding Boxes (AABBs)

95 Obstacle detection is primarily handled by retrieving the axis-aligned bounding boxes (AABBs) of
96 each object using PyBullet's `getAABB` function. The `map.py` file contains functions for extracting
97 these bounding boxes:

- 98 • `get_bbox(id)`: This function retrieves the AABB for each link of a given object, identified
99 by its id. It iterates over all link IDs (including the base link) and collects the corresponding
100 AABBs.
- 101 • `get_navigation_map(robot, plot=True)`: This function aggregates the AABBs of all
102 obstacles in the environment, excluding the robot and the floor. It iterates over all object
103 IDs, using `get_bbox` to obtain their bounding boxes, which are stored in the list `ob_bboxes`.
104 If plotting is enabled, it visualizes these obstacles on a 2D map using Matplotlib, aiding in
105 debugging and visualization.

106 3.3.3 Constructing a Static Occupancy Map

107 A static occupancy map represents the navigable space and obstacles in the environment in a grid
108 format. The construction process is as follows:

- 109 • **Grid Resolution and Size:** The environment is discretized into a 2D grid based on a
110 specified resolution (e.g., 0.05 meters per grid cell). The grid covers the dimensions of the
111 environment (e.g., from `-x_max` to `x_max` and `-y_max` to `y_max`).
- 112 • **Inflating Obstacles:** To account for the robot's size and ensure safe navigation, the bounding
113 boxes of obstacles are inflated by a certain number of grid cells (`inflate_cells`). This
114 creates a buffer zone around each obstacle, preventing the robot from planning a path too
115 close to them.
- 116 • **Marking Occupied Cells:** For each inflated obstacle bounding box, the corresponding grid
117 cells in the `static_map` array are marked as occupied (`value = 1`). The map effectively
118 distinguishes between free space (0) and obstacles (1).
- 119 • **Validation:** The start and goal positions are converted to grid coordinates, ensuring they lie
120 within the environment's boundaries and are not located on obstacles.

121 3.4 Path Planning Using the A* Algorithm

122 3.4.1 Grid-Based Graph Representation

123 The A* planner operates on a graphical representation of the environment. The graph construction
124 process is as follows:

- 125 • **Creating a 2D Grid Graph:** A 2D grid graph is created using NetworkX's `grid_2d_graph`,
126 where each node represents a grid cell in the occupancy map.
- 127 • **Removing Obstacle Nodes:** Nodes corresponding to occupied grid cells (obstacles) are
128 removed from the graph, effectively marking them as non-traversable areas.

129 3.4.2 Implementing the A* Algorithm

130 In environments with narrow gaps, such as that between a bed and cabinet, traditional path planning
131 algorithms like PID control, which assume the robot moves in a straight line along its current heading,
132 may not be sufficient. This is because the robot may become obstructed if it cannot change its
133 orientation to navigate through such confined spaces. To address this, we propose a two-phase A*
134 path planning approach, specifically designed to guide the robot through narrow gaps by adjusting its
135 orientation during navigation.

136 • **Path Planning in Two Phases:** The path planning process is divided into two distinct
137 phases:

138 – **Phase 1: Start to Narrow Gap:** In this phase, the robot follows the A* algorithm to
139 navigate from the start position to a point just before the narrow gap. At this stage, the
140 robot continues in its forward direction, but upon reaching the gap, it must transition
141 to a sideward orientation (i.e., perpendicular to its previous heading) in order to pass
142 through the gap.

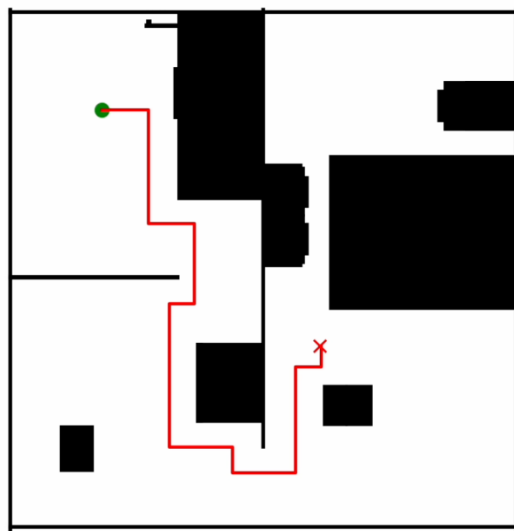


Figure 1: Phase 1

143 – **Phase 2: Sideways Navigation through Gap to Goal:** Once the robot reaches the
144 intermediate position (the green-marked point) just before the gap, its orientation is
145 adjusted to a sideward direction. The robot then continues to move through the gap in
146 this new orientation, following the A* path until it reaches the goal.

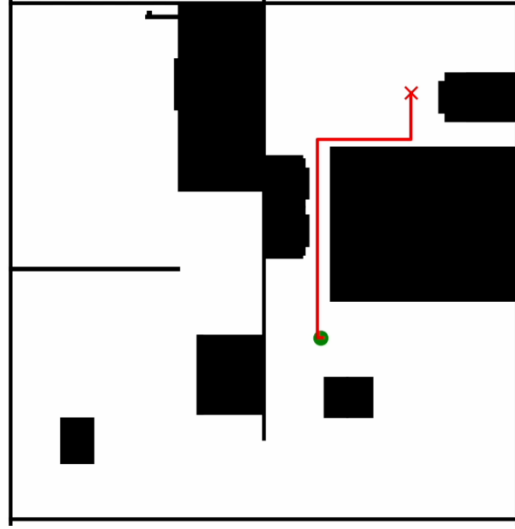


Figure 2: Phase 2

• Algorithm Implementation:

- **Initialization:** The AStarPlanner class is initialized with parameters such as robot size, obstacle boundaries, grid resolution, and visualization preferences. The robot's path is planned in two stages as described above.
- **Path Finding:** In the first phase, the A* algorithm is used to find the shortest path from the start position to the point just before the narrow gap. Upon reaching this point, the robot is instructed to switch to a sideward orientation. In the second phase, the algorithm computes a new path, now assuming that the robot is side-facing, from the narrow gap to the goal position.
- **Orientation Adjustment:** At the intermediate point (the green marker), when the robot transitions from the first phase to the second, it adjusts its orientation from forward-facing to side-facing. This transition is critical for allowing the robot to traverse through the narrow gap. The robot continues along the new path in this adjusted orientation.
- **Visualization:** If enabled, the planner visualizes the environment, including the static map, start and goal positions, narrow gap, and the planned path. The intermediate point (where the robot switches orientation) is marked clearly in the visualization, which assists in debugging and verifying the path planning process.

This two-phase path planning approach ensures that the robot can effectively navigate through tight spaces by dynamically adjusting its orientation, overcoming limitations posed by traditional PID-based control methods.

3.4.3 Ensuring Efficient Navigation

The A* algorithm ensures the robot finds the most efficient path by simultaneously considering the cost to reach a node and the estimated cost to the goal. By inflating obstacles and using a fine grid resolution, the planner takes into account the robot's size and navigation constraints, preventing collisions and optimizing path length.

3.5 Obstacle-Avoiding Navigation

The RobotController class in move_robot.py manages the robot's movement along the planned path:

- **Initialization:** The controller is initialized with the robot's initial pose, the planned path to follow, and parameters such as the PID controller for smooth motion.
- **Navigation to Waypoints:**

- 178 – **Waypoint Iteration:** The robot navigates sequentially to each waypoint along the
179 planned path.
- 180 – **Yaw Adjustment:** Before moving to a waypoint, the robot adjusts its yaw to face the
181 target direction, ensuring the movement aligns with the path.
- 182 – **Motion Execution:** The robot uses a simplified PID controller to compute neces-
183 sary adjustments based on the distance to the target, with the `sim_action` function
184 incrementally updating the robot’s position to ensure smooth and controlled motion.
- 185 – **Collision Avoidance:** By following the path generated by A*, the robot inherently
186 avoids obstacles. Additionally, the path planning process accounts for the robot’s size,
187 maintaining a safe distance from obstacles.

188 3.6 Manipulation

189 The initialization of the mug position is within a 0.15 by 0.2 area at the top surface of the drawer. The
190 drawer is initialized with the first cabinet open. Hence, the robot does not have to open the drawer
191 before picking the mug.

192 A deterministic procedure could be derived from the environment setup and the task requirements.
193 First, the robotic arm should raise above the mug’s height to get ready for the picking task and also
194 avoid collisions with the mug or drawer. From observing the setup, the drawer’s back side is against
195 wall and right side is next to the bed. Therefore, the robot may only approach the mug from the front
196 or left side of drawer. If the robot move towards the mug in the front side of the drawer, it may collide
197 with the open cabinet and close it, so robot needs to keep a distance from the drawer at the front side.
198 Hence, it is more feasible and stable to approach the drawer from its left. Even if the robot collide
199 with the drawer, there is minimal impact on the pick and place operation. Since the drawer’s left side
200 is along X direction, the robot could move along Y direction until its X position is beside the drawer’s
201 left side, assuming that the drawer location and dimensions are known. Then, the robot should turn
202 and move along X direction to get to the left side of drawer and move to Y position of the mug. The
203 robot should be facing X direction at this moment and is to the left, or Y direction of the mug. Since
204 the stretch direction of the robot is perpendicular to its motion direction, the gripper could reach the
205 mug from the left side of the drawer by adjusting the stretch. The gripper position is adjusted to
206 be above the mug’s position and the opening space of the gripper is towards the edge of the mug,
207 aided by the `get_mug_pose()` method from the provided tools. Then the gripper is lowered such
208 that the end effector link is almost touching the top edge of the cup to grasp the mug. The point of
209 contact for grasping is fine tuned to be the bottom side edge of the mug when viewing from top,
210 with one gripper finger inside the mug and the other outside. The gripping action is performed using
211 the `attach()` function from tools. Although this method is using a constraint to simulate gripping
212 instead of applying physical friction on the object to really grasp it. This simplification is sufficient in
213 the fixed simulation environment and also makes it more practical to implement. After picking up the
214 mug, the robot could simply move in -X direction until the mug is above the open drawer. Lower the
215 gripper and releasing it to place the mug in the drawer. The task is completed.



Figure 3: Picking the mug

4 Discussion

4.1 Navigation

The navigation task was implemented successfully, but several iterations were required to address various challenges encountered. The first challenge was selecting an appropriate path-planning method. Initially, we explored with Dijkstra's algorithm but ultimately adopted the A* algorithm for its efficiency and ease of implementation. The second challenge was obstacle avoidance during path planning. Early attempts saw the robot colliding with obstacles. Also the narrow space formed between the bed and the cabinet on the wall opposite the bed proved particularly problematic. These issues were resolved through fine-tuning the A* algorithm and adjusting the robot's orientation when navigating tight spaces. The robot's direction is reversed before passing the bed to avoid the robotic arm colliding with the cabinet. Lastly, the robot's motion was initially very slow. This was addressed by implementing customized motion control functions and incorporating a simplified PID controller to improve speed and accuracy in motion controls. These adjustments ensured successful task completion with enhanced performance.

4.2 Manipulation

As for the manipulation task. The current solution using fixed procedure works well with the fixed environment. However, the limitation on this method is that this analysis of the trajectory and action planning is done manually. Hence, it is not generalizable to random or real-world environments. For instance, it will not work if the drawer is turned to face sideways or if the drawer is moved to the other side of the bed. Another difficulty is the simulation of gripping effect. Current implementation relies on the `attach()` function from the tools. As this function only sets a constraint to fix the relative position of the end-effector link and the cup, it demonstrated random behavior on the orientation of the mug. In addition, as the default constraint is applied at the center of each object, the mug would crash into the gripper. The reason is the origin point of the mug is inside its body at its center of mass and the gripper opening dimension is not wide enough to cover the outer diameter of the mug. Also, it seems the axis definition of the mug's urdf file is not aligned with its orientation placed in the simulation, as it is rotated during the initialization process. As a result of above factors, the mug rotates randomly when attached to the end effector. After the `detach()` method is called, the mug gets stuck by the end effector link and gripper fingers and the place operation could not be completed. The `attach()` method is improved to include constraints on the mug's orientation and set the correct relative positions between the mug and the end effector, such that the mug's top edge is slightly below the end effector link and is in between the two gripper fingers. With the improved `attach()` function, the simulation animation looks smooth and the mug falls naturally due to gravity after calling `detach()` function.

5 Potential Improvements

The current implementation of navigation uses a static map obtained from the simulation. This approach assumes known environment but in a real-world dynamic environment, real-time obstacle detection is crucial. To address this challenge, the path planning system needs to continuously update the occupancy map based on sensor data, such as LiDAR and cameras. This means the robot must be able to detect changes in the environment and re-plan its path based on newly detected or moved obstacles. For example, when sensors detect a new obstacle, the path planner will adjust the original path in real time to avoid collisions and ensure safe navigation. To achieve this, the algorithm must handle sensor data noise, make reasonable inferences about dynamic changes in obstacles, and generate new feasible paths. As technology advances, robots will be able to adapt to real-time changes in more complex and uncertain environments, enhancing their flexibility and efficiency in dynamic settings.

There are two aspects in the manipulation task that could be enhanced. First, inverse kinematics and trajectory planning should be implemented for the robot to autonomously wield its arm and gripper to reach target locations. For this simple project, the current deterministic procedure practical, due to its easy implementation within short time schedule and relatively stable performance. However, as it is not transferrable to apply on any other tasks, proper trajectory planning and inverse kinematics should be deployed. It could be conducted analytically or using machine learning models [10]. Second,

268 more realistic simulation of gripping mechanism could be introduced by implementing gripper finger
269 control with contact and friction forces. Current method of grasping relies heavily on the constraint
270 functionality from Pybullet, which does not reflect real interaction between objects. This solution also
271 makes too much simplification on the gripper action control. There is no control on the motions of
272 the gripper fingers. A simulation that captures the physical mechanism of closing the gripper fingers
273 and applying contact forces to create friction with the object would better represent the physical
274 dynamics of grasping. This simulation may also improve the robot performance. For example, the
275 robot could detect distance between the fingers or the torque on the gripper motor to examine if any
276 object is grasped, if an object is too heavy, the simulation could also simulate the fall of the object.

277 Lastly, more advanced features could be incorporated from the vision capabilities. Current robot
278 control algorithms does not fully utilize the vision abilities provided by the cameras mounted on the
279 robot. The visual processing could allow the robot to gain more information about the environment.
280 The robot may use camera input to detect and avoid obstacles in navigation tasks. Also, the robot
281 could make automatic action planning if the image of the environment could be perceived. For
282 example, if the robot is able to see the drawer is closed, it could plan actions to open the drawer first
283 and pick mug afterwards.

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289 have little prior experience in the robotic field and the solution proposed is still preliminary, we really
290 enjoyed this learning opportunity. The process allowed us to gain deeper insights on robotics. We are
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