# Autonomous Trash Collection System with Mobile Manipulation

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# Introduction



### Problem

- Current cleaning robots lack efficient, robust, and scalable navigation.
- Limited adaptability in dynamic environments.

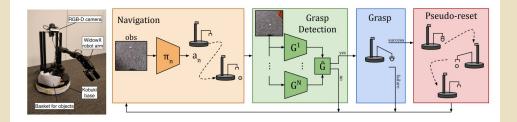
## **Our Approach**

- Vision-guided navigation and manipulation.
- Reinforcement learning (RL) for training navigation and manipulation policies.

### Goal

- Develop a scalable, efficient, and adaptable cleaning robot.
- Test state-of-the-art RL-based methods in real-world scenarios.

# **Related works**



# Fully Autonomous Real-World Reinforcement Learning with Applications to Mobile Manipulation.

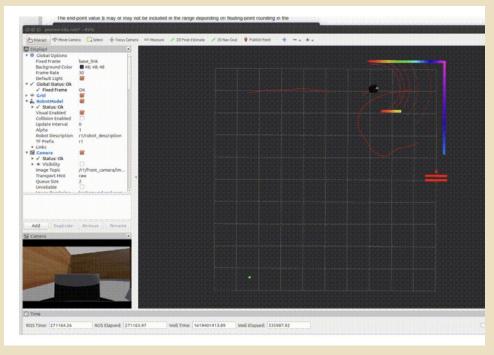
Deep reinforcement learning training separate navigation and grasping policy Reward given to navigation policy when the robot grasps an object or initiates a grasp action

> [Charles Sun, Jedrzej Orbik, Coline Devin, Brian Yang, Abhishek Gupta, Glen Berseth, and Sergey Levine. Conference on Robot Learning, 2021]

# **Related works**

**Goal-Driven Autonomous Exploration Through Deep Reinforcement Learning** 

Reinis Cimurs, II Hong Suh, Jin Han Lee



# Methods

### **Navigation Policy:**

- RL-based policy trained for dynamic environments.
- Inputs: Simulated camera images for real-time decisions.
- Pre-trained policies used for robust navigation.

### **Grasping Policy**:

- Traditional ROS and Movelt-based pipeline for object manipulation.
- Reliable gripper control for successful grasping tasks.

### Hybrid Approach:

- Combines RL for adaptability with traditional methods for reliability.
- Ensures flexibility and performance stability in varying scenarios.

# Input

- Camera
- Sensor

### RL Navigation

- Obstacle Avoidance
- Path Planning

### Trash Detection

 HSV color space for target identification Movelt Grasping Policy

 Trajectory Planning for Object Manipulation

# OUTPUT

 Trash Collection and Disposal

# Environment

#### Gazebo Simulation Setup

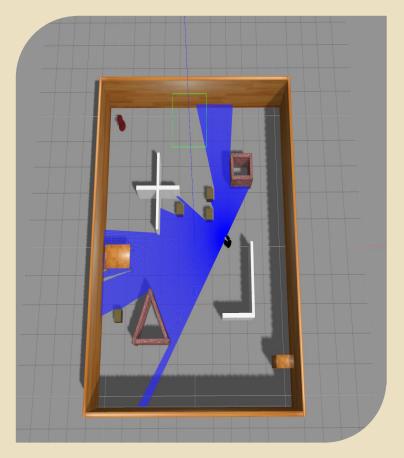
- **Platform:** Gazebo integrated with ROS for realistic indoor scenarios.
- Features:
  - Dynamic obstacles (tables, walls, narrow pathways).
  - Randomly placed trash items of various shapes and colors.

#### **Environment Components**

- Camera Integration:
  - Onboard camera captures real-time images for trash detection and navigation.
- Gripper:
  - Simulated gripper for object manipulation and trash collection.

#### **Dynamic Scenarios**

• Moving obstacles and repositioned trash to test adaptability and robustness.



# Progress

### Achievements

- Successfully set up Gazebo simulation environment integrated with ROS.
- Implemented a vision-guided navigation policy with reinforcement learning.
- Developed a **Movelt-based grasping pipeline** for object manipulation.

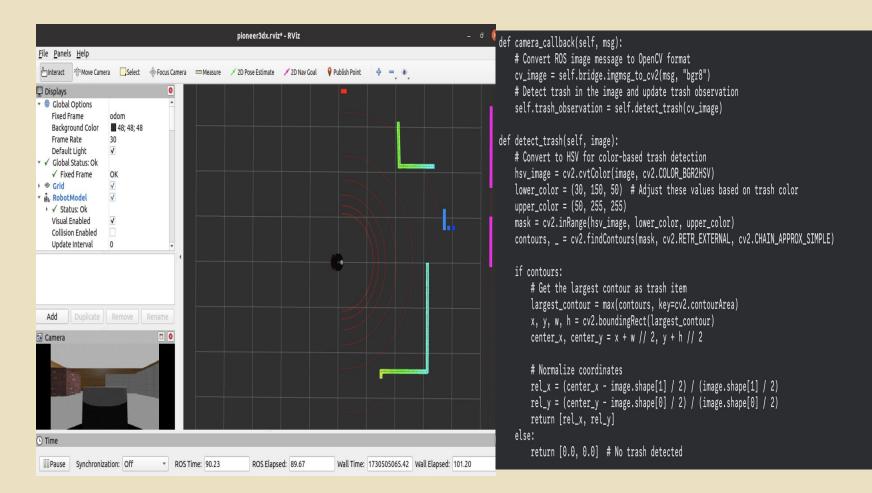
### Progress

- Navigation Policy
  - RL policy demonstrates consistent performance in dynamic environments.
  - Initial success in avoiding obstacles and reaching target locations.
- Movelt Pipeline

#### Current Status:

The Movelt-based grasping pipeline has been designed to handle predefined object grasping tasks reliably. However, the code is still in the early stages of development and not fully functional. Current implementation struggles with adapting to objects of varying sizes and positions.

- Challenges and Errors:
  - a. **Grasp Accuracy:** Difficulty in detecting the exact position of objects or inaccuracies in calculating position coordinates.
  - b. Error Messages: Unexpected failures in path planning or gripper control, reported by Movelt or ROS.
  - c. **Robot Control:** The gripper fails to fine-tune its approach at the target, either missing the object or approaching at an incorrect angle.



# Detect if the goal has been reached and give a large positive reward if distance < GOAL\_REACHED\_DIST:</pre>

target = True
done = True
# Add Trash Manipulation logic here
if done:

rospy,loginfo("Goal reached. Initiating trash manipulation...")
manipulator = TrashManipulator() # Instantiate the TrashManipulator
manipulator.run() # Perform trash collection task
rospy,loginfo("Trash manipulation complete.")
robot\_state = [distance, theta, action[0], action[1]]
state = np.append(laser\_state, self.trash\_observation)
reward = self.get\_reward(target, collision, action, min\_laser)
return state, reward, done, target

Code added to previous source code -env setting

Code we added to gripper - grasp trash manipulation

import rospy from moveit\_commander import MoveGroupCommander, roscpp\_initialize, roscpp\_shutdown from sensor\_msgs.msg import Image from cv\_bridge import CvBridge import cv2 class TrashManipulator: def \_\_init\_\_(self): # Initialize ROS node rospy.init\_node("trash\_manipulator", anonymous=True) # Initialize MoveIt roscpp\_initialize(sys.argv) self.arm\_group = MoveGroupCommander("arm") self.gripper\_group = MoveGroupCommander("gripper") # Camera setup self.bridge = CvBridge() rospy.Subscriber("/camera/rgb/image\_raw", Image, self.camera\_callback) self.trash\_position = None def camera\_callback(self, msg): """Detect trash using the camera feed.""" try: cv\_image = self.bridge.imgmsg to cv2(msg, "bgr8") hsv\_image = cv2.cvtColor(cv\_image, cv2.C0LOR\_BGR2HSV) lower\_color = (30, 150, 50) # Adjust based on trash color upper\_color = (50, 255, 255) mask = cv2.inRange(hsv\_image, lower\_color, upper\_color) contours, = cv2.findContours(mask, cv2.RETR EXTERNAL, cv2.CHAIN APPROX SIMPLE) if contours: largest\_contour = max(contours, key=cv2.contourArea) x, y, w, h = cv2.boundingRect(largest\_contour) center\_x, center\_y = x + w // 2, y + h // 2 self.trash\_position = (center\_x, center\_y) except Exception as e: rospy.logerr(f"Error in camera callback: {e}") def move\_to\_trash(self):
 """Move the arm to the detected trash position.""" if self.trash position: rospy.loginfo("Moving to trash position...") target pose = self.arm\_group.get\_current\_pose().pose target\_pose.position.x = self.trash\_position[0] / 100.0 target\_pose.position.y = self.trash\_position[1] / 100.0 target\_pose.position.z = 0.1 # Adjust height self.arm\_group.set\_pose\_target(target\_pose) success = self.arm group.go(wait=True) if success: rospy.loginfo("Arm reached the target. Grasping...") self.grasp\_trash() def grasp\_trash(self): """Grasp the detected trash.""" self.gripper\_group.set\_named\_target("closed") self.gripper\_group.go(wait=True) def release\_trash(self): """Release the trash into the bin.""" self.gripper group.set\_named\_target("open") self.gripper\_group.go(wait=True) def run(self): """Main loop.""" rospy, loginfo("Starting trash manipulation...") while not rospy.is\_shutdown(): if self.trash position: self.move to trash() self.grasp\_trash() rospy.sleep(2) # Simulate moving trash self.release\_trash() break rospy.sleep(1) # Wait for trash to be detected if \_\_\_name\_\_ == "\_\_\_main\_\_": try: manipulator = TrashManipulator() manipulator.run() except rospy.ROSInterruptException: pass

finally:

roscpp\_shutdown()

# Planning

#### **Refine Navigation Policy:**

- Continue to improve the RL-based navigation policy for more efficient pathfinding and robust collision avoidance in dynamic environments.
- Address current challenges in handling complex obstacle arrangements.

#### Enhance Grasping Mechanism:

- Debug and optimize the Movelt pipeline to improve grasping success rates, focusing on varied object shapes, sizes, and positions.
- Integrate feedback from testing to fine-tune grasping parameters and improve adaptability.

#### Integrate System Components:

- Establish seamless interaction between the navigation policy and grasping mechanism to ensure coordinated operation.
- Address synchronization challenges between RL-based navigation and Movelt-based manipulation.

#### **Evaluate Performance:**

- Conduct final trials in the simulation environment to measure key performance metrics, including:
  - 1. Trash detection accuracy.
  - 2. Grasp success rate.
  - 3. Navigation efficiency and overall task completion time.
- Compare performance across different object types and environmental conditions to validate robustness.

# REFERENCE

[1] Charles Sun, Jedrzej Orbik, Coline Devin, Brian Yang, Abhishek Gupta, Glen Berseth, and Sergey Levine. Fully Autonomous Real-World Reinforcement Learning with Applications to Mobile Manipulation. Conference on Robot Learning, 2021.

[2] Max Bajracharya, James Borders, Richard Cheng, Dan Helmick, Lukas Kaul, Dan Kruse, John Leichty, Jeremy Ma, Carolyn Matl, Frank Michel, Chavdar Papazov, Josh Petersen, Krishna Shankar, and Mark Tjersland. Demonstrating Mobile Manipulation in the Wild: A Metrics- Driven Approach. Robotics: Science and Systems XIX, Robotics: Science and Systems Foundation, July 2023.

[3] Daniel Honerkamp, Tim Welschehold, and Abhinav Valada. Learning Kinematic Feasibility for Mobile Manipulation through Deep Reinforce- ment Learning. IEEE Robotics and Automation Letters, 6: 6289–6296, 2021.

[4] Reinis Cimurs. DRL-robot-navigation, GitHub. Available: <u>https://github.com/reiniscimurs/DRL-robot-navigation</u>.

# Thank you