

Abstract

A mobile manipulator for intelligent object retrieval is presented. The system was integrated using state of the art R&D hardware and software, which implemented autonomous navigation, object recognition, and object pose estimation based optimal grasping.

The retrieval of an object of interest is commanded that involves subsequent object detection and recognition while autonomously navigating using the known map and starting from an arbitrary position. From close proximity, object pose estimation based optimal grasp is selected to pick up the object. The object is retrieved back to the start position in this scenario.

Near perfect results for all subtasks in object retrieval are achieved that can be improved using better perception models.

Introduction

This work is motivated generally by the search, and material handling operations in the manufacturing and warehousing applications to name a few, as have been addressed in recent few works [1-4]. This boils down to the problems of intelligent mobile navigation and manipulation in structured and semi-structured static environments. A mobile manipulation system is developed by integrating a mobile robot with a robotic manipulator. This system includes peripherals to improve visual functions. The software framework leverages ROS 2, Gazebo, and NVIDIA's Isaac Sim, facilitating the creation of an AI-based control system in a simulated environment.

Research Questions

1. How can we effectively **integrate** a mobile wheeled robot and a robotic manipulator?
2. What is the best way for autonomous **navigation**?
3. How can we incorporate object **recognition** capability to this mobile manipulator?
4. How can we best implement the **pose** estimation and **grasp** selection for autonomous object retrieval?

Materials and Methods

Hardware:

Turtlebot3 [5] Waffle Pi
Open ManipulatorX (OMX)

Software:

ROS 2 Humble
Gazebo Simulator
NVIDIA Isaac Sim

Methods:

- The Nav2 library is used for the autonomous navigation system, implementing a behavior tree based algorithm to handle planning and control.
- The YOLOv8 model is used for target identification and grasping, providing object bounding box classification using a CNN.
- The MoveIt2 library will perform pose estimation and grasp selection using point clouds to determine object location and proper grasp trajectory.



Image source:
http://roboskileo.com/img/cms/erafika/TB3_Waffle_Pi_OpenManipulator.jpg

Modeling and Simulation:

Robot Operating System and Gazebo

- Control of each individual joint was achieved using libraries provided by ROS 2.
- Path planning and joint trajectory was prototyped with user input.
- Simulation in custom virtual worlds was performed to test the system.
- Programmed nodes were created with Python to have the robot execute a series of actions

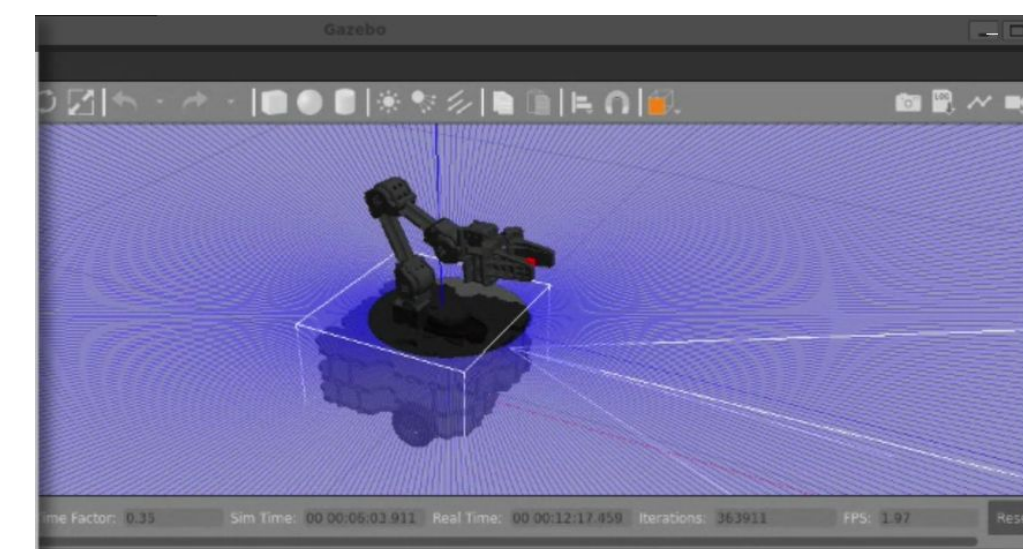


Figure 1: TB3 and OMX based mobile manipulator model performing a user-set pose in the GAZEBO simulation environment

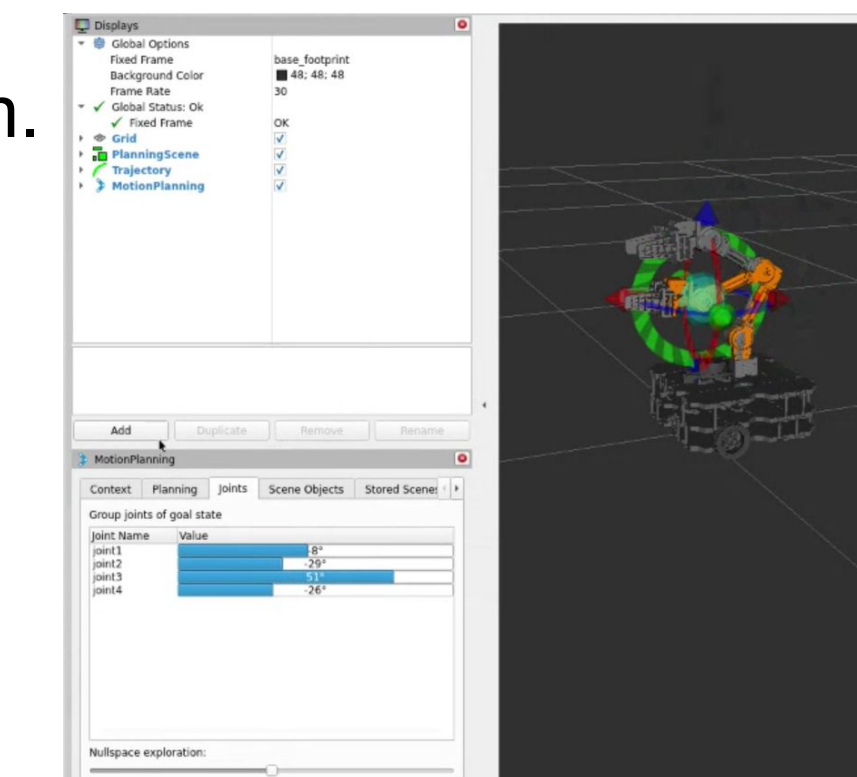


Figure 2: path planning and joint trajectory using ROS2-provided resources.

NVIDIA Isaac Sim

- Isaac Sim accesses a computer's Nvidia GPU for better sensor tests and virtual environment.
- The values and connections of each joint were edited directly with the simulation interface.
- Control of the mobile base was performed with an action graph and CLI interface.
- Different sensors were implemented to the base model with Isaac Sim's vast library of supplemental components.

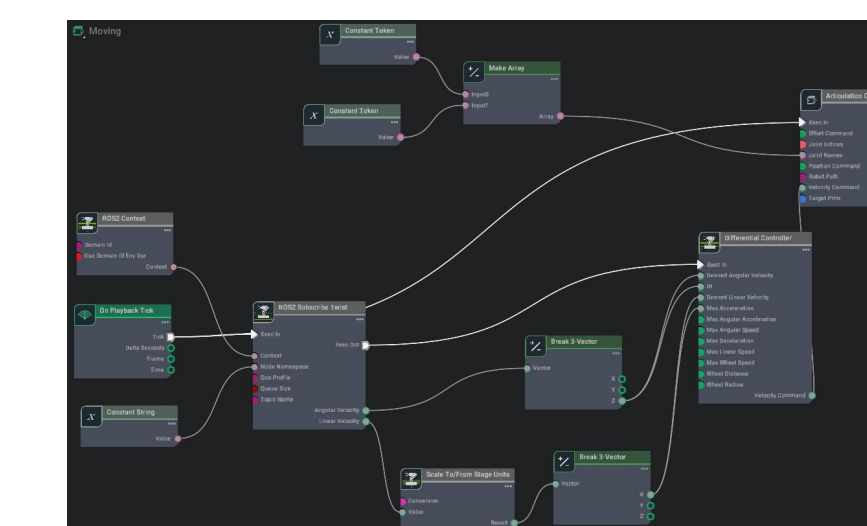


Figure 3: Example of action graph in ISAAC SIM

Navigation:

- The Nav2 library is used for autonomous navigation, taking a user defined point and angle and planning a path to it from the start location.
- The Nav2 algorithm is based on modular task servers that communicate with a behavior tree.

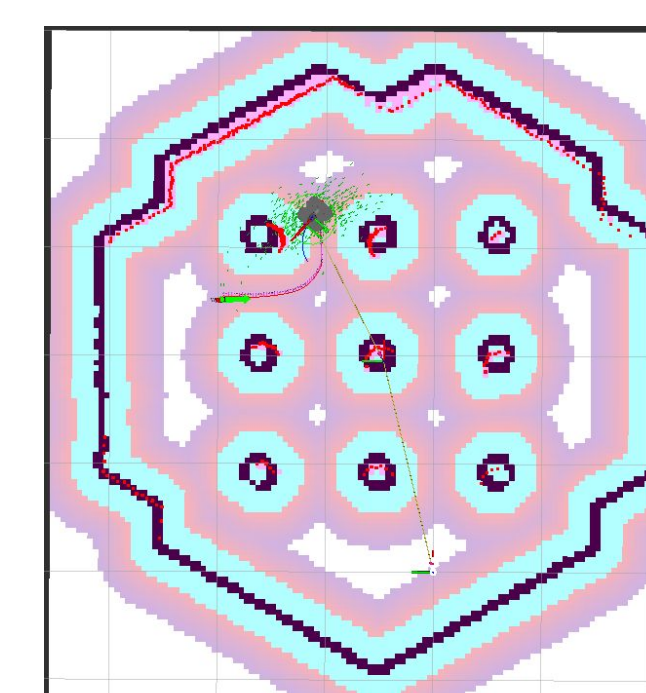


Figure 4 (left): mobile manipulator planning a path to a user specified point.

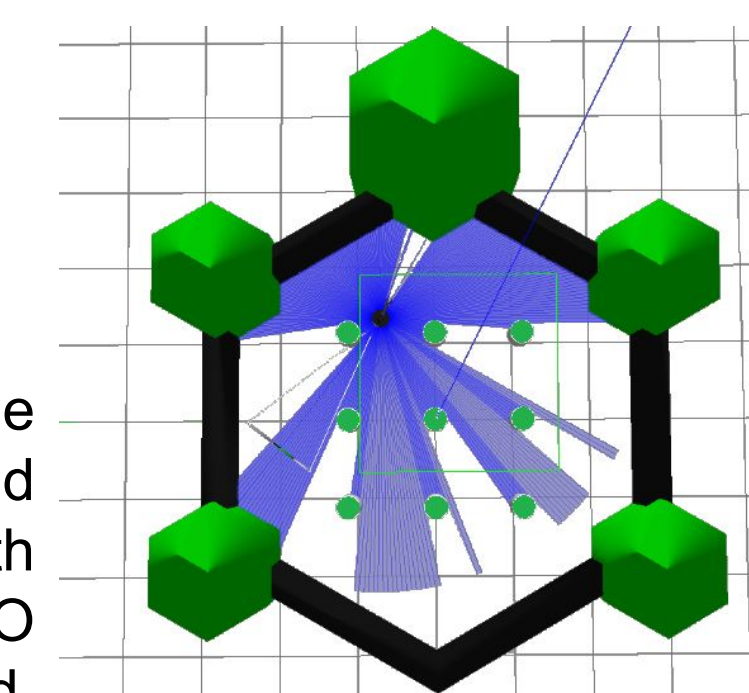


Figure 5 (right): machine vision perception and execution of the path planning in a GAZEBO test world.

Object Recognition:

- Object recognition is implemented using the CNN YOLOv8 model.

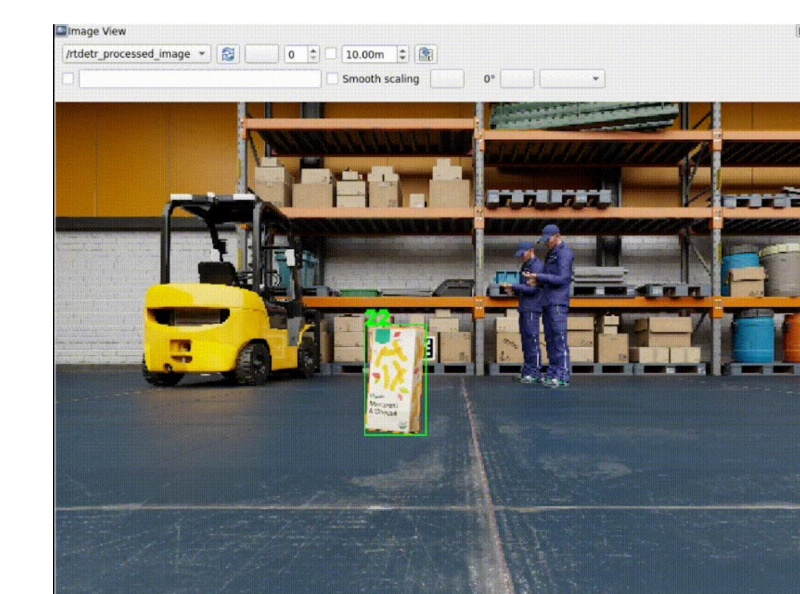


Figure 7: Object detection result by using Isaac ROS Object Detection Package

Pose Estimation and Grasp Selection

- Grasp selection is implemented with the MoveIt2 library, which produces potential positions and orientations that the end effector may assume in order to grasp the target item.

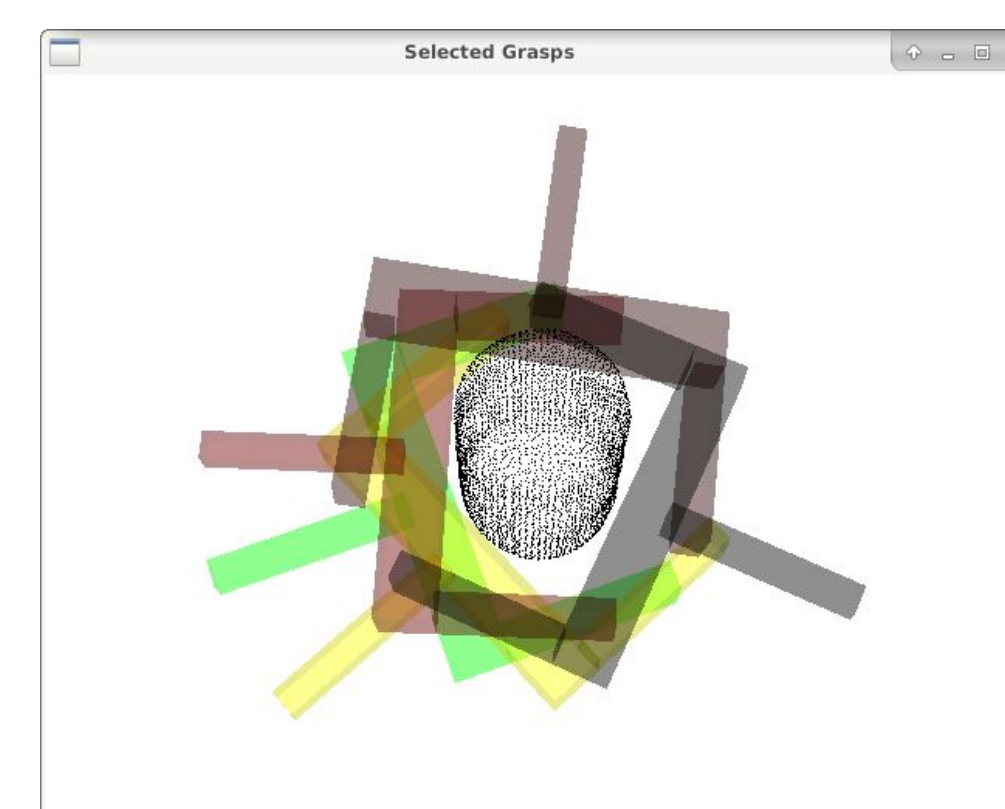
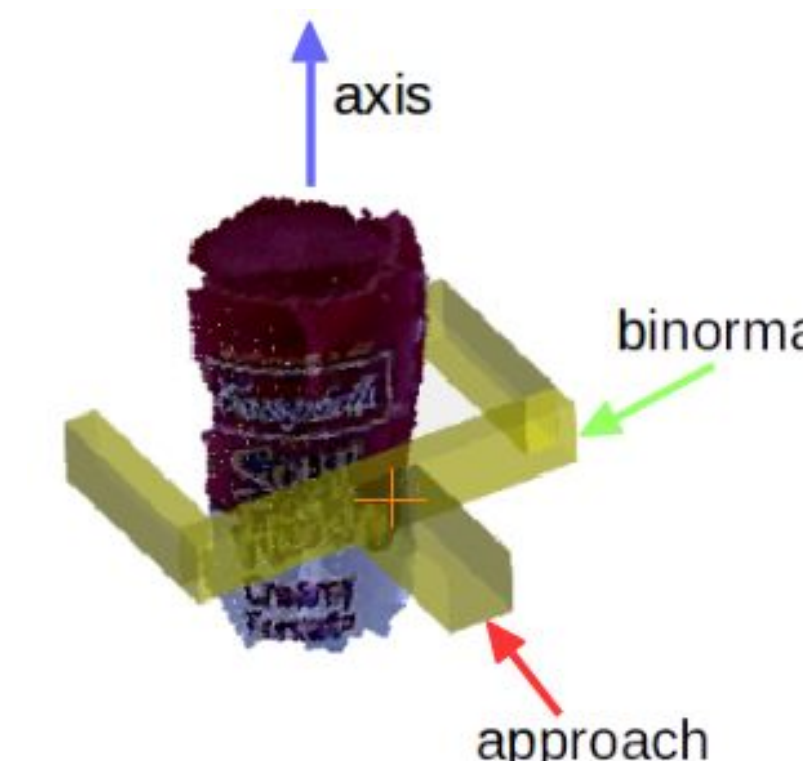


Figure 7 (left): potential grasp poses output by the MoveIt2 library surrounding a targeted object.

Figure 8 (right): optimal grasp selection for a targeted object decided by MoveIt2.



Conclusions

A mobile manipulator for intelligent object retrieval is modelled and simulated that is able to do the autonomous navigation, object recognition, and pose estimation based grasp selection. A behavior based planning using decision tree in a static structured environment is used. Oriented bounding boxes are used for object recognition. The grasping selection using intelligent pose estimation is implemented.

A perfect navigation to the object of interest, and the accuracies of object recognition and grasp selection resulted as 86% and 82% respectively. The experimentation indicates that the object recognition and pose estimation models are pivotal for real-world object retrieval applications.

Our future work will include the object retrieval task in the non-structured and cluttered environments.

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<https://github.com/WM-3-Intelligent-Robot-Arm/wm3ira.github.io>

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Results

- Autonomous navigation functionality has a 100% accuracy with behavior tree based planning.
- The CNN model based object recognition has an accuracy of 86%.
- The mobile manipulator determines a correct grasp based on pose estimation 82% of the time.



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