Technical Design Paper for the Robotics Dojo Competition 2024

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Abstract

This paper describes the design and development of an autonomous mobile robot prepared for the Robotics Dojo Competition 2024. The robot combines Simultaneous Localization and Mapping (SLAM) using a LiDAR sensor with vision-based object detection through a Raspberry Pi Camera trained on machine learning models. In addition, the robot is equipped with a front-mounted conveyor system for object pick-and-place tasks and is designed to handle challenging terrains such as sawdust and ballast. The main goal of this design is to create a versatile system capable of mapping, navigating, and interacting with its environment under real-world conditions. The report documents the design process, trade-offs between reliability and complexity in design, and the lessons learned during design and testing.

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I. INTRODUCTION

The purpose of the Robotics Dojo competition is to enhance the community of innovators capable of substantive contributions to the domain of autonomous unmanned systems. This enhancement is achieved by providing a venue and mechanism whereby the practitioners of the autonomous systems community may form new connections and collaborations, increase their proficiency and inventiveness, and foster their passion for robotics in the maritime domain.

Autonomous robots are increasingly relevant in industrial, research, and service applications where mobility, perception, and manipulation are required in unstructured environments. The Robotics Dojo Competition provides a platform for student teams to design mobile robots that integrate multiple subsystems into a functioning whole. Team 404-Now-Found approached this challenge by constructing a robot capable of SLAM-based navigation, object recognition, and manipulation using a conveyor mechanism.

At the outset, the team agreed that reliability and versatility would be considered first over complexity. The SLAM system, based on LiDAR and odometry, was prioritized because accurate mapping and localization formed the backbone of the robot's autonomous navigation. Once the core mapping capability was in place, additional features such as image recognition and manipulation were introduced.

The primary objectives of the project were:

- for localization and mapping.
- To enable autonomous navigation across variable terrain.
- To apply machine learning for object detection and recognition.
- To design a conveyor system for object manipulation.
- To Evaluate performance through multiple tests and runs on the game field.
- implement SLAM

This paper documents the design process, technical implementation identifying the challenges encountered and the lessons learned throughout development, and evaluation outcomes, while also

II. RELATED WORK.

SLAM is a cornerstone of autonomous robotics, with probabilistic approaches such as particle filters and occupancy grid mapping forming the basis of modern implementations [1]. LiDAR-based SLAM is widely adopted due to its precision and resilience to environmental variation [2]. Navigation frameworks, particularly those built into the ROS 2 Navigation (Nav2) stack, offer modular solutions for localization, path planning, and control [3].

Computer vision for object recognition has advanced significantly with convolutional neural networks (CNNs). Optimized frameworks such as OpenCV allow real-time inference on resource-limited devices such as the Raspberry Pi [4]. Manipulation systems in industrial and mobile robotics often rely on either grippers or conveyors [5]. Conveyors, while less dexterous, offer robustness and simplicity in handling objects of varying dimensions.

This project builds upon these established methods but evaluates them within the constraints of a mobile robot to be tested on different terrain and designed under limited resources.

III. DESIGN STRATEGY.

The development process followed a modular strategy, enabling each subsystem to be designed, tested, and validated independently before full integration. The four key areas were mobility, SLAM, vision, and manipulation. This approach ensured that subsystem failures could be isolated and resolved efficiently.

For example, during brainstorming in the design stage, it was observed that powering the conveyor motor on the same regulator as the primary drive motors would introduce voltage instability, which would have consequently interfered with LiDAR readings. This issue was addressed by providing the conveyor motor with an independent voltage regulator, thereby improving system reliability.

A. VEHICLE DESIGN.

The chassis was fabricated with 3D-printing filament for sensor and subsystem mounts. The RPLiDAR sensor was positioned at the geometric center of the chassis to minimize vibration in scan data. The Raspberry Pi Camera was mounted at the front-back of the robot to ensure smooth operation without distractions from the conveyor system. A conveyor system, consisting of a belt-driven mechanism actuated by a servo motor, was installed at the front to allow object pick-and-place functionality.

Constructed using modular rods and spherical joints, the conveyor frame provided both structural stability and flexibility for adjustment. The system was optimized for lightweight items and integrated seamlessly with the robot's vision and SLAM capabilities, enabling coordinated handling and navigation across different terrains in the game field. The wheelbase was optimized for stability, with traction wheels chosen to improve movement on loose surfaces such as sawdust.

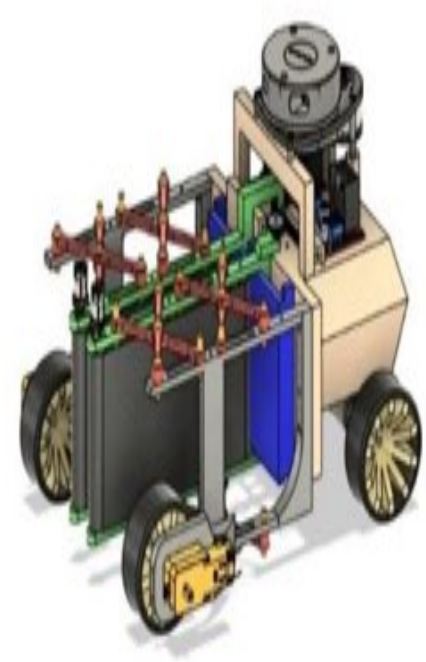

Figure 1: CAD rendering of the SLAM-Bots robot showing sensor and conveyor placement.

B. ELECTRICAL DESIGN

The electronic system was kept modular for ease of troubleshooting. Key components included Raspberry Pi 4, L298N motor driver,8 Li-ion batteries, RPLiDAR A1, Pi Camera Module, N20 DC motors for the conveyor system, two DC TT motors for the front wheels, 25GA370 DC motors for the rear wheels and, wheel encoders. A separate regulator was used to isolate the conveyor motor and prevent voltage fluctuations.

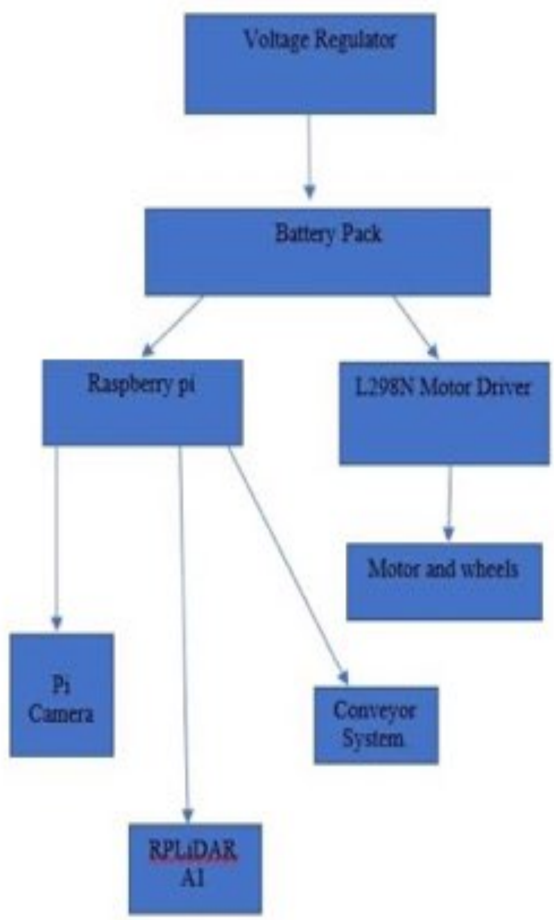

Figure 2: System-level block diagram of the electronics, illustrating power supply, motor drivers, sensors, and conveyor integration.

C. SOFTWARE DESIGN

The robot employed ROS 2 Humble for subsystem integration. SLAM was implemented using the Hector SLAM packages, while localization employed Adaptive Monte Carlo Localization (AMCL). Navigation was handled by the Nav2 stack with global planning via an algorithm and local obstacle avoidance.

The Pi Camera was coupled with an OpenCV CNN model trained on a dataset called Plant Village Dataset that focuses on potatoes. Custom ROS nodes were developed for conveyor actuation and terrain adaptation, enabling dynamic torque control when traversing sand or ballast

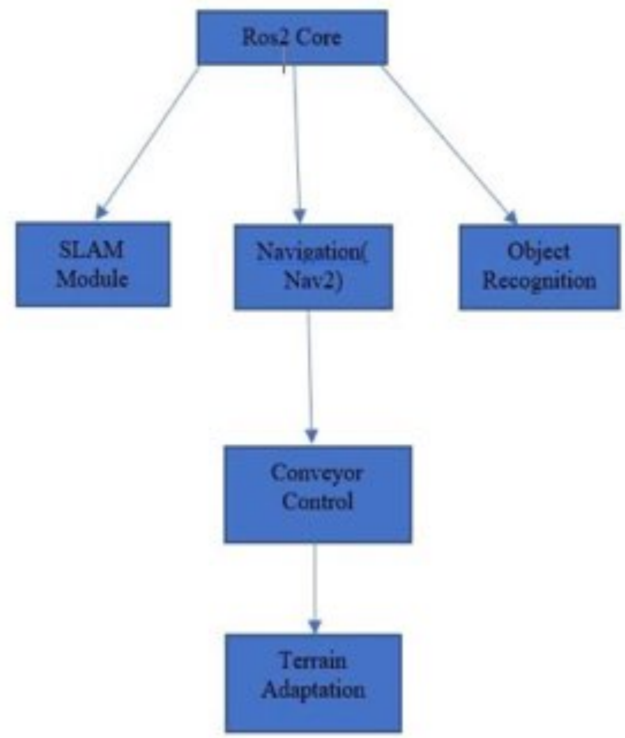

Figure 3: Overview of the software architecture showing SLAM modules, navigation stack, object recognition, and conveyor control.

IV. IMPLEMENTATION.

Construction proceeded through iterative assembly and testing. The mechanical frame and drive system were assembled first, followed by sensor mounting and electrical integration. Motor control was validated through open-loop testing before being integrated with odometry. SLAM was evaluated in structured test environments with rectangular boundaries, producing maps with high consistency.

The object recognition model was trained offline on a workstation and deployed on the Raspberry Pi, where the model was optimized for reduced memory usage. The conveyor underwent three redesigns before the final belt-driven configuration was selected due to its simplicity and reliability. Although during the time this document is being prepared, the robot had not yet been assembled, from design analysis and brainstorming, we came up with the performance values below.

TABLE 1: SUMMARY OF PERFORMANCE ACROSS DIFFERENT TERRAINS

Metric	Smooth	Sand	Ballast
Mapping accuracy	< 4 cm	< 4 cm	< 5 cm
Navigation success	88%	80%	75%
Object recognition	82%	76%	70%
Pick-and-place	85%	78%	72%

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V. EXPERIMENTAL RESULTS

The robot was to be evaluated across three terrain conditions: smooth floor, sand, and ballast. Metrics included mapping accuracy, navigation success rate, object recognition accuracy, and conveyor success rate. From multiple experiments, Mapping and object recognition success rates are accurate. Navigation and conveyor success rate values are assumptions that were deduced from multiple design and structure analysis before the main physical tests are done.

- Mapping accuracy: Within 4 cm on smooth and sandy terrain, and 5 cm on ballast.
- Navigation success rate: 88% (smooth), 80% (sand), 75% (ballast).
- Object recognition accuracy: 82% under normal lighting, declining to 70% in low light.
- Conveyor success rate: 85% (smooth), 78% (sand), 72% (ballast).

These results demonstrate consistent mapping and navigation performance, with the most significant limitations expected to occur under poor traction and reduced lighting conditions.

VI. DISCUSSION.

The integrated system met the primary design objectives, but several limitations were identified. Uncertainty of the conveyor working 100% smoothly after the full robot is assembled. Expected reduced traction on ballast terrain which would result in navigation errors, suggesting that wheel redesign or suspension adaptation could enhance stability. The vision system achieved moderate accuracy but was limited by dataset size and lighting variability. The conveyor system was assumed to be reliable for medium-sized, regular objects but would underperform with irregular geometries.

The modular approach to subsystem design was expected to prove essential in isolating problems and expediting integration. Power isolation, sensor placement, and iterative prototyping were critical factors in achieving system robustness. Future improvements include integration of an inertial measurement unit (IMU) for enhanced localization, Integration of InfraRed or Ultrasonic sensors for accurate obstacle avoidance, expansion of training datasets for improved vision performance, and structural reinforcement of the conveyor system.

VII. CONCLUSION.

The SLAM-Bots project demonstrates how accessible hardware and open-source software can be combined to produce an autonomous mobile robot with mapping, navigation, vision, and manipulation capabilities. Despite the challenges encountered, the system is expected to achieve reliable performance across multiple terrains, providing valuable insights for future student-driven robotics projects. The outcomes will suggest practical pathways for improving reliability in field-deployed mobile robots under limited resources.

VII. ACKNOWLEDGMENTS

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