Development of a Smart Lawnmower with a Mapping System Utilizing GPS and LiDAR Technology

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ABSTRACT

This paper reports on the design, implementation, and field evaluation of an autonomous lawnmower that combines GPS, IMU, and LiDAR sensing within a ROS2-based control architecture to support real-time mapping, path planning, and obstacle avoidance. The hardware platform and control architecture are outlined, including a PID motor controller and an Extended Kalman Filter used for multi-sensor fusion. Two navigation configurations; Nav2 paired with the SLAM Toolbox and Nav2 paired with GPS are evaluated and compared in terms of lawn-mowing accuracy, obstacle-avoidance performance, and the ability to pass through narrow gaps. Over six outdoor trials per configuration, the SLAM Toolbox attained a mean navigation accuracy of 88.6% (SD = 7.9%), significantly higher than the 62.1% (SD = 11.1%) mean accuracy achieved by the GPS-based configuration (Welch's t-test, $t = 4.76$, $p = 0.001$); nevertheless, because GPS-based navigation does not depend on fixed structural landmarks, it proved more robust for open-field operation. The SLAM Toolbox also recorded a perfect 100% (6/6) obstacle-avoidance success rate against 80% (8/10) for GPS, and was able to pass through gaps as narrow as 40 cm. Environmental testing further showed that LiDAR mapping quality was affected by ambient light, with noise levels lower during night-time trials. Together, these results point to a trade-off between the mapping precision offered by SLAM and the landmark-independence offered by GPS, and they motivate future work on RTK-GPS integration, full-coverage path planning, and camera-based sensor fusion to strengthen robustness for open-field lawn maintenance.

Keywords: autonomous lawnmower, GPS, LiDAR, SLAM, ROS2, Nav2, obstacle avoidance.

INTRODUCTION

Rapid progress in autonomous systems has reshaped many industries, including outdoor automation and precision lawn care. Conventional lawn maintenance is labor-intensive, time-consuming, and often yields inconsistent results. In addition, combustion-engine mowers remain a notable source of air pollution, with consequences for both human health and the surrounding environment [1]. A shift toward cleaner, automated alternatives is therefore important for advancing sustainable technology and safeguarding terrestrial ecosystems.

Even with these technological gains, an important gap persists. Autonomous lawnmowers that depend only on basic GPS and IMU modules struggle to detect and avoid dynamic obstacles with high precision, and they generally do not take full advantage of LiDAR-based processing for reliable outdoor navigation. An integrated system is therefore needed—one capable of navigating complex outdoor terrain autonomously, cutting grass accurately, and avoiding obstacles in real time.

In response to these challenges, this study describes the development of a smart lawnmower that combines GPS, IMU, and LiDAR technologies within a ROS2 framework. The research specifically aims to build a lawnmower fitted with GPS and IMU modules together with a LiDAR sensor for autonomous navigation, to integrate these components into a coherent mapping and path-planning algorithm, and to evaluate the resulting system's performance in terms of area coverage, obstacle-avoidance accuracy, and overall efficiency. The work is scoped to hardware integration, algorithm development for dynamic track adjustment and obstacle detection, and extensive outdoor testing. Because of current battery-capacity limitations, the prototype's operational coverage is capped at a maximum area of 100 square meters.

LITERATURE REVIEW

Efforts to automate lawn maintenance date back to early robotic mowers built around Arduino microcontrollers, ultrasonic sensors, and line-following methods to traverse predefined areas while avoiding collisions [2], [3]. Other researchers have developed specialized platforms using high-accuracy Local Positioning Systems (LPS) with active beacons [4], as well as propeller-assisted spiked-wheel designs capable of handling slopes as steep as 60 degrees [5]. The incorporation of the Internet of Things (IoT) has broadened operational flexibility further, enabling remote control of lawnmowers through Android applications and Bluetooth terminals [6]–[8]. A separate body of work has pursued green-energy solutions, proposing solar-powered lawnmowers fitted with color sensors and Proportional–Integral–Derivative (PID) controllers that detect grass and regulate motor speed while reducing environmental pollution [9]–[12].

Notwithstanding these mechanical and control advances, reliable outdoor navigation continues to pose a substantial challenge. Most autonomous lawnmowers depend heavily on Global Positioning Systems (GPS), which are prone to signal disruption, latency, and positional errors, particularly in obstructed environments or when operating at varying speeds [13]–[17]. Fusing GPS with Inertial Measurement Units (IMUs) has become a common way to preserve positional accuracy during signal dropouts. Recent approaches in this space include using vehicle dynamic models with velocity as an observation value [18], adaptive cascaded Kalman filtering for GPS/MEMS-IMU fusion [19], and four-wheel independent-drive steering kinematics to correct accumulated inertial drift [20].

Advanced mapping algorithms and Real-Time Kinematic (RTK) GPS have also been widely explored to improve routing efficiency and positional accuracy. Some studies apply Artificial Neural Networks (ANN) to predict horizontal GPS errors, substantially improving correct segment identification [21], while others use Fuzzy Cognitive Maps (FCM) to predict Differential GPS (DGPS) corrections [22]. Graph structure learning has likewise been used to derive accurate road networks from noisy GPS trajectory data through global optimization [23]. In the specific context of autonomous lawnmowers, coverage path-planning algorithms combined with RTK positioning have achieved collision-free routing with a low path-duplication rate of roughly 150% [24], and trajectory tracking has been improved using sliding-mode controllers based on vehicle kinematics [25].

More recent work has combined Light Detection and Ranging (LiDAR) sensing with the Robot Operating System 2 (ROS2) to build precise, real-time 3D maps and improve dynamic obstacle avoidance [26]–[28]. The move from ROS1 to ROS2 brought the Data Distribution Service (DDS) middleware, offering a decentralized, fault-tolerant architecture with lower latency and stronger real-time performance [29]. Within this ecosystem, 2D and 3D LiDAR sensors have become central to spatial mapping, using pose-graph construction and phase correlation to estimate motion [15].

These sensors are often paired with camera data—through algorithms such as YOLOv8 or Haar cascades—to achieve precise object detection and distance estimation [13], [25]. Underpinning many of these software developments is the Nav2 stack, which relies on behavior trees to coordinate tasks such as Simultaneous Localization and Mapping (SLAM), sensor fusion, and path planning, and has proven effective for mobile robots operating in both indoor and outdoor settings [16], [30]–[36].

METHODOLOGY

Development of the autonomous lawnmower proceeded through a structured process covering hardware

assembly, software configuration, and extensive field testing. The subsections that follow describe how these components were integrated and the experimental procedures used to validate the resulting system.

System Architecture and Hardware Integration

The lawnmower's hardware architecture is built around a centralized processing scheme to support efficient operation and precise control. A Raspberry Pi 4 Model B serves as the main processing unit, responsible for running the navigation algorithms, handling sensor data, and issuing velocity commands. Environmental perception is provided by a YDLidar X3 Pro sensor, which captures 360-degree distance measurements in real time, together with a Yahboom 10-axis Inertial Measurement Unit (IMU) and a Yahboom GPS module that supply continuous orientation and global positioning information. An Arduino Nano acts as a secondary microcontroller, linking the main processing unit to the physical actuators. Mobility is provided by 12V worm motors fitted with encoders and controlled through an L298N motor driver, while a high-torque 795 DC motor drives the cutting mechanism. The entire system is powered by a 12V 6000mAh lithium battery and protected by an emergency safety switch and a 15A fuse.

Control Systems and Mathematical Modeling

To translate algorithmic commands into physical movement, the Arduino Nano implements a closed-loop Proportional-Integral-Derivative (PID) control algorithm. This algorithm regulates the motor speed by continuously calculating an error value e(t) between the target velocity setpoint and the actual encoder feedback. The standard control output u(t) is applied through the following equation:

$$u(t) = K_P e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt}$$

By parsing the tuning parameters KP, Ki, and Kd directly from the main processor, the system ensures stable and accurate wheel velocity. Simultaneously, to mitigate sensor noise such as wheel slippage, the navigation framework deploys an Extended Kalman Filter (EKF). The EKF handles the non-linear kinematics of the lawnmower by utilizing a state transition model f to predict the current state based on the previous state and control input, as follows:

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_k)$$

Continuous fusion of IMU readings, motor-encoder feedback, and GPS coordinates allows the EKF to filter out slip-induced errors and keep the odometry frame highly accurate.

Software Configuration and Operational Workflow

The software stack runs on Ubuntu 24.04 using the ROS2 Jazzy distribution, chosen for its decentralized architecture and dedicated GPS waypoint-following services. Execution follows a fixed sequence: the ROS2 environment is initialized and Nav2 parameters are loaded; as GPS and IMU data stream in continuously, the EKF fuses these inputs into filtered coordinates, with a Navsat Transform node used for mapping in place of traditional Adaptive Monte Carlo Localization (AMCL).

Once localization is established, Nav2 computes a feasible path to the target. While navigating, the LiDAR continuously scans the surroundings; when an obstacle is detected, the system immediately triggers replanning to generate an evasive route, and otherwise maintains its trajectory until the target is reached, completing the autonomous run. Real-time monitoring and visualization throughout this process are handled by RViz2 and Foxglove WebSockets.

Experimental Testing Environments

To validate the integrated system, experiments were carried out across both structured indoor settings and varied outdoor terrain. Testing included a direct lawn-mowing task over a 3-meter indoor path and a 5-meter outdoor path, with six trials run for each configuration (rosbag2, Nav2 SLAM, and Nav2 GPS); the rosbag2

tool was used to record and replay velocity-command topics so that path deviation and navigation success could be measured accurately. Navigation accuracy for each trial was computed as Accuracy (%) = (1 − Lateral Error / Path Length) × 100, with lateral error taken as the distance between the lawnmower's final position and its intended set point. The system's dynamic response was further evaluated through obstacle-avoidance tests using static objects placed in the planned path—six trials for the SLAM configuration and ten for the GPS configuration—and through gap-navigation tests in which the lawnmower was required to pass through narrow structural gaps ranging from 30 cm to 120 cm in width, each tested once, to probe the system's precision and limits in confined spaces. Figure 1 and Figure 2 present the overall system block diagram and the hardware prototype, respectively.

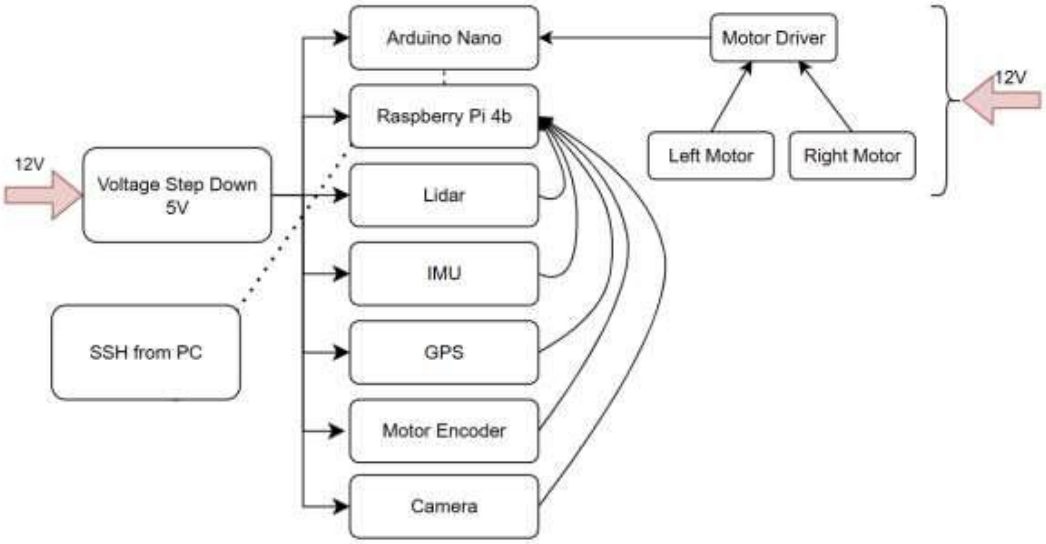


Figure 1: Systems Block Diagram



Figure 2: Autonomous Lawnmower Prototype

Known Hardware and System Limitations

Several hardware and software constraints should be kept in mind when interpreting the results above. The Yahboom GPS module fitted to this prototype is a consumer-grade receiver: under open-sky conditions it typically achieves positional accuracy of 3-5 m, but this can degrade to 10-20 m in obstructed real-world settings, and is a major contributor to the lower, more variable accuracy seen in the GPS-based trials. Processing latency can also arise from the Arduino Nano under heavier computational load, and the closed-loop PID controller's behavior is sensitive to how its Kp, Ki, and Kd gains are tuned—tuning that proved time-consuming to optimize across different operating conditions. Wheel odometry is similarly prone to drift from slippage and uneven ground, making accurate odometry-to-world frame transformations in ROS2 essential

for reliable navigation. A Raspberry Pi Camera Module is included in the hardware for potential vision-based obstacle detection, but it cannot run at the same time as the LiDAR sensor because of bandwidth limits on the Raspberry Pi 4B, so the camera was left unused during the navigation trials reported here. Finally, the 12V lithium battery's efficiency and cycle life may be affected by extreme outdoor temperatures despite its built-in protection circuits. These constraints are revisited in the Conclusion and Future Work section.

RESULTS AND DISCUSSIONS

Lawn Mowing Navigation: SLAM vs. GPS Performance

Performance on the core lawn-mowing task depended strongly on which localization method was used. Over six outdoor trials, the Nav2 SLAM Toolbox configuration reached a mean navigation accuracy of **88.6% (SD = 7.9%)** (**Figure 3** shows the full spread), with individual trial results ranging between 73.8% and 96.6%. One trial stood out with accuracy falling to **73.8%**, a result traced to severe wheel slippage while crossing high grass that introduced a large slip error into the odometry frame; even so, the SLAM Toolbox was able to recalibrate using environmental features and correct the map frame, largely compensating for the mechanical odometry shift. By comparison, the Nav2 GPS-based configuration averaged **62.1% (SD = 11.1%)** across its six outdoor trials, with individual results spanning **40.6%** to **72.2%** (**Figure 4**).

A Welch's two-sample t-test confirms that the SLAM Toolbox's outdoor accuracy significantly exceeded that of the GPS-based configuration ($t = 4.76$, $p = 0.001$, $n = 6$ per group). These navigational errors are attributable mainly to the limited accuracy of the consumer-grade GPS module—typically rated at 3-5 m under ideal conditions but degrading to 10-20 m in obstructed settings—together with drift in the IMU's magnetometer. A further anomaly was a consistent rightward drift of the lawnmower during operation, even though the RViz visualization misleadingly showed a straight trajectory; this drift is attributed to GPS and odometry inaccuracies, although a mechanical cause such as wheel misalignment was not independently tested and cannot be ruled out.

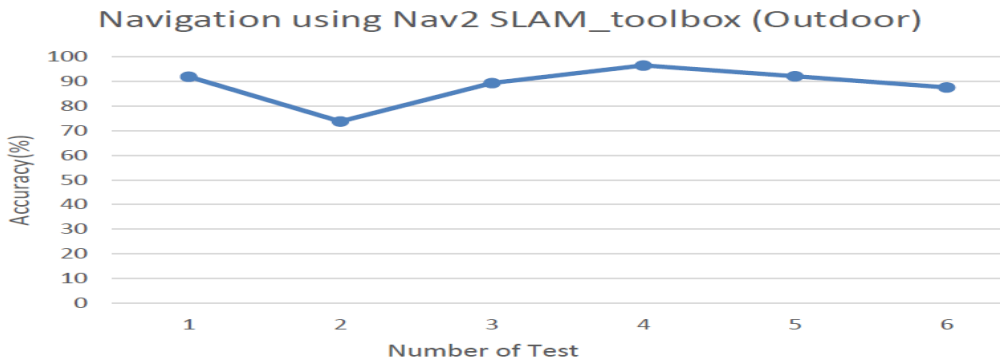


Figure 3: Accuracy of Navigation using Nav2 SLAM Toolbox (Outdoor)



Figure 4: Accuracy of Navigation using Nav2 GPS (Outdoor)

Environmental Light Interference on LiDAR Mapping

Environmental conditions had a marked effect on data quality during the outdoor GPS and SLAM tests. The YDLidar X3 Pro sensor proved highly sensitive to ambient light levels: trials run in the afternoon and evening showed noticeably higher noise, which the system mistakenly registered as physical obstacles. This false-positive obstacle detection kept forcing the Nav2 system to replan its path, extending task completion times. Night-time trials, by contrast, showed markedly less noise and produced a clean, accurate costmap that supported much smoother navigation, as shown in **Figure 5**. It should be noted that afternoon, evening, and night trials were not run under otherwise matched conditions—ambient temperature, humidity, and wind were neither controlled nor logged—so some of the observed difference in noise may stem from factors other than light alone.

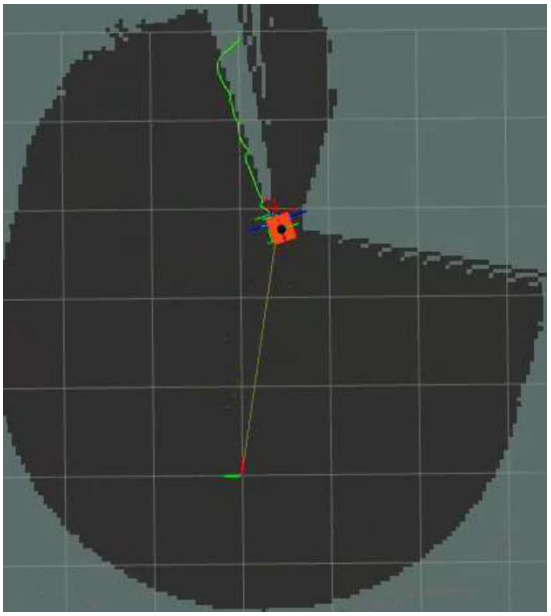


Figure 5: Test During Night Time

Obstacle Avoidance Anomalies under GPS

In the obstacle-avoidance trials, the Nav2 SLAM Toolbox configuration succeeded in all six attempts, consistently steering around static obstacles without failure. The Nav2 GPS configuration, by contrast, succeeded in **80%** of trials (8 of 10), as shown in **Figure 6**. The **20%** failure rate points to specific weaknesses in the system's localization: failures were mainly driven by the rightward drift noted earlier and by imprecise initial GPS calibration. Without stable reference points to anchor the map frame, stationary obstacles ahead of the mower appeared to move within the RViz visualization, which desynchronized the Nav2 path planner and sent it into a repeated cycle of generating new evasive routes until the task eventually timed out and failed. For comparison, completion times for each of the six (all successful) SLAM Toolbox trials are shown in Figure 7.

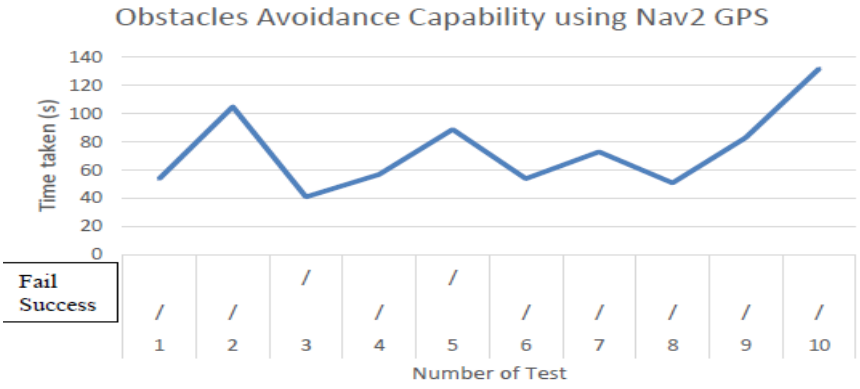


Figure 6: Obstacle Avoidance Capability using Nav2 GPS

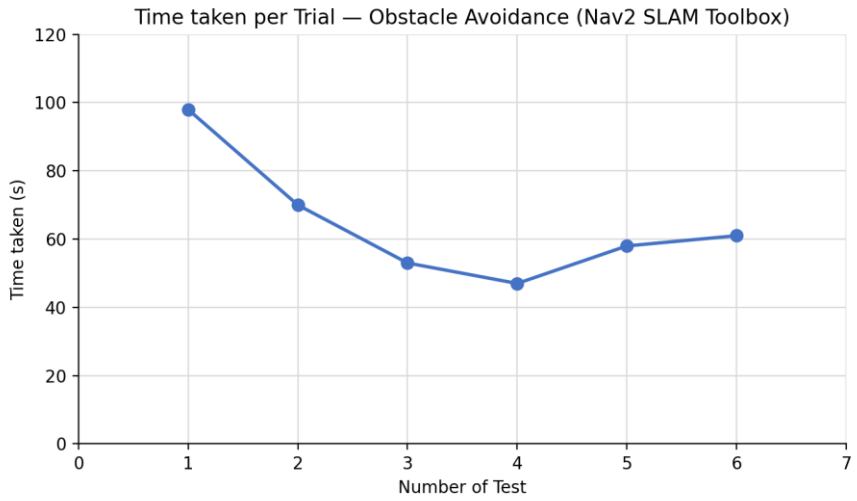


Figure 7: Time Taken per Trial — Obstacle Avoidance Capability using Nav2 SLAM Toolbox

Spatial Maneuverability and Gap Navigation Limits

The gap-navigation tests established the outer limits of the lawnmower's spatial maneuverability. Indoors, where walls offered clear reference points, the Nav2 SLAM Toolbox configuration was able to pass through gaps from **40 cm** up to **80 cm** wide, as summarized in **Figure 8**, but was unable to pass through a **30 cm** gap: at that width, the nearby obstacles fell within the system's pre-set safety margins, causing the lawnmower to keep generating alternative paths rather than attempt the gap, which eventually timed out. This indicates that, absent adjustments to cost-map parameters—such as a smaller inflation-layer radius or a reduced cost-scaling factor—the current prototype cannot be used in fields with pathways narrower than **40 cm**. Because each gap width was tested only once rather than over repeated trials, these findings should be read as indicative rather than statistically conclusive; repeated testing at each width is recommended in future work to confirm the reliability of these boundary values.

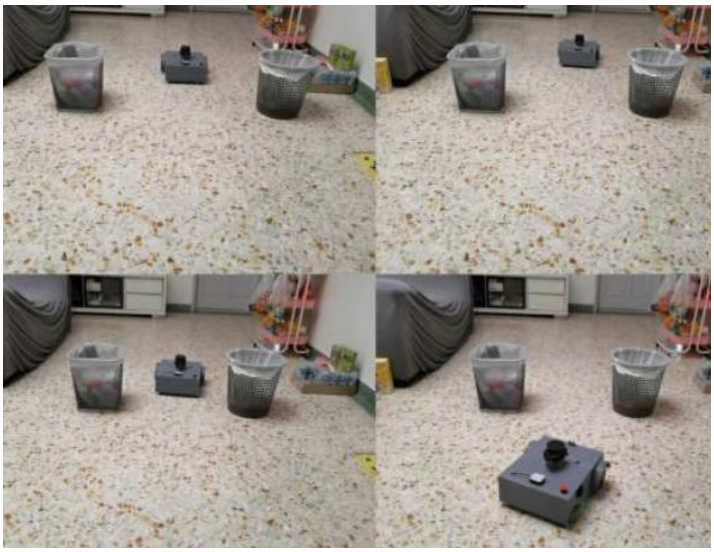


Figure 8: Results Nav2 Capability of SLAM Toolbox

A companion gap-navigation test was run for the Nav2 GPS configuration on a flat outdoor surface, with the results shown in Figure 9. This configuration successfully passed through gaps of 50 cm and above (50, 60, 80, 100, and 120 cm) but was unable to clear a 40 cm gap. Set against the SLAM Toolbox results above, this suggests SLAM can reliably handle narrower openings (down to 40 cm) than GPS (limited to 50 cm and above), consistent with SLAM's advantage of having stable structural references for recalibration, versus GPS's need for an open, landmark-free area. This underlines a broader trade-off seen throughout the study: the SLAM Toolbox is better suited to tightly constrained, structured spaces, whereas the GPS-based

configuration is better suited to open-field operation despite requiring a wider minimum clearance.

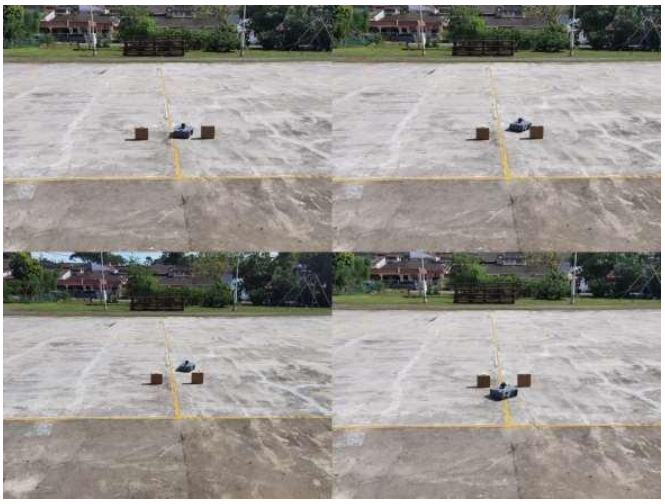


Figure 9: Results Nav2 Capability by using GPS

CONCLUSION AND FUTURE WORK

This study designed, built, and evaluated an autonomous lawnmower that combines GPS, IMU, and LiDAR sensing within a ROS2 framework, aimed at addressing the inefficiency and environmental impact of conventional lawn maintenance. Extensive field testing and a comparative analysis of navigation strategies surfaced clear operational trade-offs. The rosbag2 trajectory-tracking approach offered high precision on predefined paths but lacked the adaptability needed for real-world obstacle avoidance. The Nav2 SLAM Toolbox performed best outdoors, reaching a mean accuracy of 88.6% across six trials, a perfect obstacle-avoidance success rate, and the ability to navigate gaps as narrow as 40 cm; however, because it depends on static reference points, its reliability may drop in open fields that lack such features. The Nav2 GPS configuration, in contrast, was less dependent on environmental landmarks and therefore better suited to open-field use, though it came with a lower mean positional accuracy (62.1%), a lower obstacle-avoidance success rate (80%), and greater vulnerability to LiDAR light interference. These findings carry several caveats: the core navigation trials covered relatively short paths (3 m indoor, 5 m outdoor), each gap width was tested only once, the light-interference trials did not control for potential confounds such as temperature and humidity, and the mechanical contribution to the observed rightward drift was not tested independently.

Overall, the GPS-integrated Nav2 system offers a scalable, efficient approach that can meaningfully cut manual labor while supporting sustainable, zero-emission landscaping. Moving this technology toward commercial deployment will require addressing the localization drift and calibration issues identified here, including through the integration of Real-Time Kinematic (RTK) GPS to reach centimeter-level accuracy. Adding a full-coverage path-planning package within ROS2 would also help ensure systematic, edge-to-edge area coverage without gaps. Additional future work should include mechanical diagnostics—such as checks on wheel alignment and encoder calibration—to rule out non-GPS contributors to the observed rightward drift; extended-distance field trials to test whether the results generalize beyond the 3-5 m paths used here; and repeated trials at each gap width to obtain statistically robust boundary limits. Finally, adding camera-based image processing (for example, using OpenCV) to the existing LiDAR and IMU sensor suite would improve real-time detection of complex objects and support a more comprehensive, fail-safe navigation framework for dynamic outdoor environments. Implementing this addition will first require resolving the current bandwidth limitation that prevents the onboard Raspberry Pi Camera and the LiDAR sensor from running simultaneously—for instance, by moving one sensor stream to a dedicated interface or upgrading the single-board computer's processing and I/O capacity.

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REFERENCES

1. D. D., K., Kumar D, K., T., S., & B., S. B. (2022). Design and development of grass cutter using solar renewable energy source. In 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 113–117). IEEE.
2. Diwakaran, S., Kumar, M. D. V., Mohanreddy, P. S., Rishika, Ch., Sreenivasulu, P., & Sivasubramanian, M. (2023). Design of an autonomous mower with height adjustable cutting motor. In 2023 4th International Conference on Signal Processing and Communication (ICSPC) (pp. 348–352). IEEE.
3. Ramisetti, V., Chowdary, P. S., Bankuru, C., Peda, S., & Pasala, M. (2024). Automatic grass cutting robot using Arduino and ultrasonic sensor. In 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO) (pp. 1–4). IEEE.
4. Smith, A. D., Chang, H. J., & Blanchard, E. J. (2012). An outdoor high-accuracy local positioning system for an autonomous robotic golf greens mower. In 2012 IEEE International Conference on Robotics and Automation (pp. 2633–2639). IEEE.
5. Nishimura, Y., & Yamaguchi, T. (2023). Grass cutting robot for inclined surfaces in hilly and mountainous areas. Sensors, **23**(1).
6. Athipatla, S., Kandati, B., Kanipaku, S., & Kalluri, D. (2023). Solar powered Bluetooth controlled grass cutting robot. In 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS) (pp. 1–7). IEEE.
7. Hashiyana, V., Haiduwa, T., Suresh, N., Shishiiveni, T., & Mutalya, A. (2020). A prototype of an Android application controlled lawnmower. In 2020 IST-Africa Conference (IST-Africa) (pp. 1–5). IEEE.
8. M. K., R., V., S., K., C., R. G., R. R., D., N., & S., T. (2023). Design and implementation of IoT enabled grass cutting robot powered by solar PV system. In 2023 International Conference on Inventive Computation Technologies (ICICT) (pp. 1402–1406). IEEE.
9. A., R., A., S., A., T., B., E., P., A., & S., S. M. (2023). Electrical energy-powered grass cutter with autonomous operation and pollution mitigation. In 2023 Intelligent Computing and Control for Engineering and Business Systems (ICCEBS) (pp. 1–6). IEEE.
10. Balaganesan, S. M., Abishek, S., Aravinth, R., & Maignanamoorthy, A. S. N. (2023). Solar based grass cutter robot. In 2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS) (pp. 1676–1680). IEEE.
11. Habib, Md. R., et al. (2019). PID controller based automatic solar power driven grass cutting machine. In 2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2) (pp. 1–4). IEEE.
12. Sunanda, C. V., Gowtham, G., Pradeesha, J., & Dheeraj, K. (2024). Automated solar based electric grass cutter with multi-purpose robotic vehicle. In 2024 4th International Conference on Data Engineering and Communication Systems (ICDECS) (pp. 1–5). IEEE.
13. Hwang, G. H., Lee, S. W., & Jeon, J. (2024). ROS2 implementation of object detection and distance estimation using camera and 2D LiDAR fusion in autonomous vehicle. In 2024 IEEE 33rd International Symposium on Industrial Electronics (ISIE) (pp. 1–5). IEEE.
14. Liu, J., Sun, Q., Fan, Z., & Jia, Y. (2018). TOF lidar development in autonomous vehicle. In 2018 IEEE 3rd Optoelectronics Global Conference (OGC) (pp. 185–190). IEEE.
15. Liu, S., & Nakanishi, T. (2022). Obstacles detection and motion estimation by using multiple lidar sensors data. In 2022 13th International Congress on Advanced Applied Informatics Winter (IIAI-AAI-Winter) (pp. 196–201). IEEE.
16. Liu, Y., Lu, Y., Peng, C., Bu, Q., Liang, Y. C., & Sun, J. (2023). Autonomous vehicle based on ROS2 for indoor package delivery. In 2023 28th International Conference on Automation and Computing (ICAC) (pp. 1–7). IEEE.
17. Suherman, Pinem, M., Zardika, A., & Siregar, Y. (2020). Location misplacement analysis on global positioning system. In 2020 4th International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM) (pp. 246–249). IEEE.
18. Zhao, Yu., Yang, Zh., Song, Ch., & Xiong, D. (2018). Vehicle dynamic model-based integrated navigation system for land vehicles. In 2018 25th Saint Petersburg International Conference on Integrated Navigation Systems (ICINS) (pp. 1–4). IEEE.

19. Wang, W., Wu, Z., & Zhang, H. (2018). An adaptive cascaded Kalman filter for two-antenna GPS/MEMS-IMU integration. In 2018 IEEE/ION Position, Location and Navigation Symposium (PLANS) (pp. 833–837). IEEE.
20. Zhou, S., Zhao, P., & Jin, J. (2020). Cascaded GPS/IMU integrated positioning system based on vehicle kinematics model. In 2020 Chinese Control and Decision Conference (CCDC) (pp. 1134–1139). IEEE.
21. Hashemi, M., & Karimi, H. A. (2016). A machine learning approach to improve the accuracy of GPS-based map-matching algorithms. In 2016 IEEE 17th International Conference on Information Reuse and Integration (IRI) (pp. 77–86). IEEE.
22. Nimvari, Z. E., & Mosavi, M. R. (2017). Accurate prediction of differential GPS corrections using fuzzy cognitive map. In 2017 3rd Iranian Conference on Intelligent Systems and Signal Processing (ICSPIS) (pp. 64–68). IEEE.
23. Huang, J., et al. (2018). Automatic generation of road maps from low quality GPS trajectory data via structure learning. IEEE Access, **6**, 71965–71975.
24. Chung, C.-H., Wang, K.-C., Liu, K.-T., Wu, Y.-T., Lin, C.-C., & Chang, C.-Y. (2020). Path planning algorithm for robotic lawnmower using RTK-GPS localization. In 2020 International Symposium on Community-centric Systems (CcS) (pp. 1–4). IEEE.
25. Fan, J. (2023). Research on real-time SLAM algorithm based on ROS node. In 2023 12th International Conference of Information and Communication Technology (ICTech) (pp. 515–520). IEEE.
26. Arunkumar, P. M., Muthu, N., Prathuman, V. G., Sadham Ukkashi, A. M., & Vyshnav Achuthan, P. V. (2021). Simultaneous localization and mapping technique based autonomous lawn mower. In 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS) (pp. 767–771). IEEE.
27. Catapang, A. N., & Ramos, M. (2016). Obstacle detection using a 2D LIDAR system for an autonomous vehicle. In 2016 6th IEEE International Conference on Control System, Computing and Engineering (ICCSCE) (pp. 441–445). IEEE.
28. M., T. R., & M., A. (2019). Obstacle detection and obstacle avoidance algorithm based on 2-D RPLiDAR. In 2019 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1–4). IEEE.
29. Maruyama, Y., Kato, S., & Azumi, T. (2016). Exploring the performance of ROS2. In 2016 International Conference on Embedded Software (EMSOFT) (pp. 1–10). IEEE.
30. K., M. J., Babu, A. V., Damodaran, S., James, R. K., Murshid, M., & Warrier, T. S. (2024). ROS2 - Powered autonomous navigation for TurtleBot3: Integrating Nav2 stack in Gazebo, RViz and real-world environments. In 2024 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES) (pp. 1–6). IEEE.
31. Cen Cheng, P. D., Indri, M., Sibona, F., De Rose, M., & Prato, G. (2022). Dynamic path planning of a mobile robot adopting a costmap layer approach in ROS2. In 2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA) (pp. 1–8). IEEE.
32. Guo, J., Du, J., & Xu, D. (2018). Navigation and positioning system applied in underground driverless vehicle based on IMU. In 2018 International Conference on Robots & Intelligent System (ICRIS) (pp. 13–16). IEEE.
33. Liu, Z. (2021). Implementation of SLAM and path planning for mobile robots under ROS framework. In 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP) (pp. 1096–1100). IEEE.
34. Phueakthong, P., & Varagul, J. (2021). A development of mobile robot based on ROS2 for navigation application. In 2021 International Electronics Symposium (IES) (pp. 517–520). IEEE.
35. Rihan, Y., Zein, I., Alaraj, M., & Soudan, B. (2024). Campus courier: An autonomous delivery robot on-campus. In 2024 Advances in Science and Engineering Technology International Conferences (ASET) (pp. 1–6). IEEE.
36. Abdullah, L., Jamaludin, Z., Chiew, T. H., & Rafan, N. A. (2012). Systematic method for cutting forces characterization for XY milling table ballscrew drive system. International Journal of Mechanical and Mechatronics Engineering, 12(6), 28-33.