Design And Development of Autonomous Mobile Robot (AMR) For Land Mine Detection Using Robot Operating System

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Abstract

Increasing concern over unexploded landmines in war- torn areas necessitates the creation of safe and dependable detection systems. In this paper, an Autonomous Mobile Robot (AMR) for landmine detection is designed and implemented using the Robot Operating System (ROS). The system is designed to employ a collection of sensors, including a metal detector, LiDAR, GPS, and encoders, to map and navigate the terrain independently. Real-time mapping and localization are achieved through Hector SLAM in the robot design implemented in ROS. A URDF model of the robot is created and simulated using Gazebo to test and validate the design before actual implementation. The prototype can detect metallic objects as it moves autonomously, thus reducing human exposure in risk areas. Experimental results affirm the effectiveness of the system in simulated environments, which offers a window for implementation in minefields in the near future.

Keywords: Landmines, Demining technologies Sensor fusion, Real-time processing, Data analysis, Autonomous functionality.

Introduction

Landmines continue to pose a severe humanitarian and environmental threat in most of the world's post-conflict regions. Unexploded ordnance not only threatens civilian lives but also hinderssocio-economic development by restricting access to agricultural land, water sources, and structures. Over 5,000 people have been wounded or killed by landmines in the last few years, most of whom were children, according to the Landmine Monitor report. Despite efforts by most international organizations and governments, the demining process continues to be slow, bureaucratic, and risky.

Conventional demining activities usually involve hand probing, hand-held metal detectors, or the use of specially trained animals such as dogs and rats. Although these activities have been partially effective, they are mostly slow, subject to human error, and an enormous risk to human life. In addition, manual activities are not very extensive in coverage and scope, and it is challenging to effectively cover the scope of the problem. In the presence of such threats, a growing need is felt for intelligent autonomous systems that can aid or even replace human beings in dangerous demining operations. Robotics in the shape of Autonomous Mobile Robots

(AMRs) has gone a long way in very effectively solving this paradox. The robots can carry a host of sensors to scan the environment, detect mines, and navigate over dangerous terrain autonomously. Such developments are not only making it safer but quicker and more accurate in detection. The aim of this research is to design and develop an Autonomous Mobile Robot for landmine detection using the Robot Operating System (ROS) platform. ROS provides a

nice and platform-independent software platform to design modular, scalable, and reusable robotic systems. The designed robot is a combination of several hardware modules such as a metal detector, LiDAR, GPS module, wheel encoders, and microcontroller for sensor fusion and motion control. The system uses Hector SLAM for real-time mapping and localization in an unknown environment for the purpose of enabling autonomous navigation and systematic area coverage.

The robot is represented in Unified Robot Description Format (URDF) and simulated using Gazebo and is intended to be tested for performance in a virtual controlled environment before being deployed in the real world. The use of open-source platforms such as ROS and Gazebo also makes the system cost-effective and open for development.

This paper demonstrates a full pipeline from design idea through hardware implementation and simulation testing of a landmine-detecting robot. This solution in the paper attempts to fill the gap between traditional detection mechanisms and wholly autonomous, scalable, and safer humanitarian demining solutions.

3. System Design and Methodology

The hardware, software, and robotics technologies are integrated to make the AMR for landmine detection. The below section explains each subsystem and methodology in detail.

3.1 Hardware Architecture Hardware Architecture

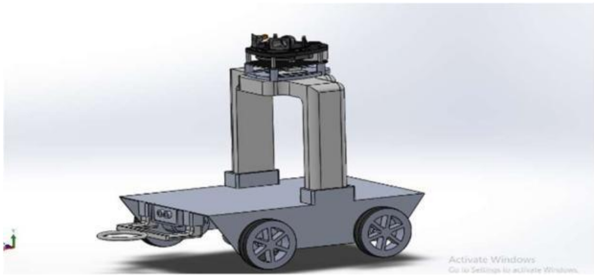

Fig.3.1 Hardware Architecture of AMR

The Autonomous Mobile Robot (AMR) hardware platform is robust, outdoor environment capable and designed for optimal integration of sensing,computing, and actuation components. The foundation is a four-wheel differential drive platform powered by four 12V DC geared motors with high torque and stability for harsh surfaces. Each wheel has encoders mounted on it to supply real-time odometry feedback. It runs on a 12V lithium-ion battery and features a power supply of an isolated and stable voltage lines to logic circuits and motor drivers. The Arduino Mega 2560 microcontroller directly interfaces the motors, encoders, and analog sensors, executing real-time commands such as speed control and PWM signal modulation. A Raspberry Pi 4B, on board the robot, acts as the highest-level processing node, running ROS Noetic and carrying out high-level tasks like SLAM, navigation, logging data and sensor data fusion.

The primary sensors include RP-LiDAR A1 for environmental scanning, a NEO-6M GPS module for global localization, and a specially created metal detector sensor mounted at the front.

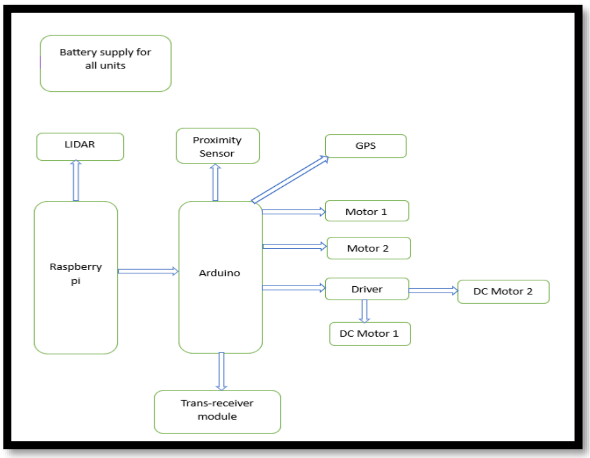

Fig 3.2 Block diagram of the receiver module

These sensors are linked by serial, I2C, and GPIO connections to the Arduino and Raspberry Pi, forming a robust and dependable sensor- actuator network.

Software Architecture

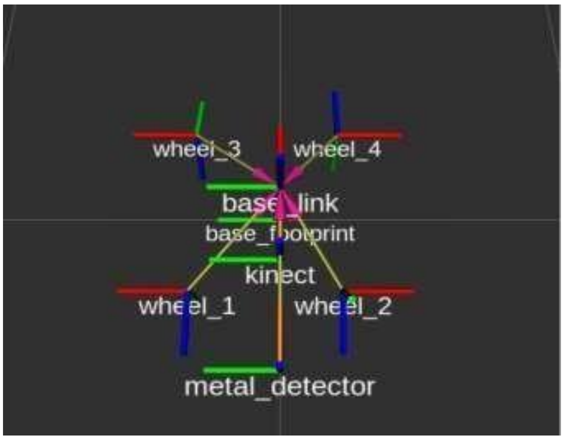

Fig 3.3 Software Architecture

The software architecture of the system is implemented with Robot Operating System (ROS) Noetic to facilitate a distributed, modular, and scalable robotics platform. The system consists of individual ROS nodes for acquiring sensor data, processing, control logic, and visualization. URDF (Unified Robot Description Format) is used to represent robot configuration in terms of all the physical components, sensor placements, and joint configurations. Sensor nodes such as LiDAR (rplidar_node) and GPS (nmea_navsat_driver) publish data at a fixed interval to some ROS topics. Spatial relationships between different coordinate frames such as base link, laser_frame, gps_frame, and metal_detector_frame are established by a tf transform tree. Odometry is published by the motor controller node and can be fused with GPS data using the robot_localization package for improved pose estimation. The global and local planners are combined in the move_base node to get around, and the rviz visualization tool provides real-time feedback on sensor outputs, robot path, and detection events. Each of the software components is launched with ROS launch files, so the system is extremely configurable and tunable.

Detection and Marking

Landmine detection system includes a customized metal detector in the front portion of the robot. The detector senses variations in the magnetic field caused by embedded pieces of metal, generally resulting from landmines. Once the detection occurs, the occurrence is processed and released to the ROS topic /metal_detected which triggers an interrupt to the process of the robot.

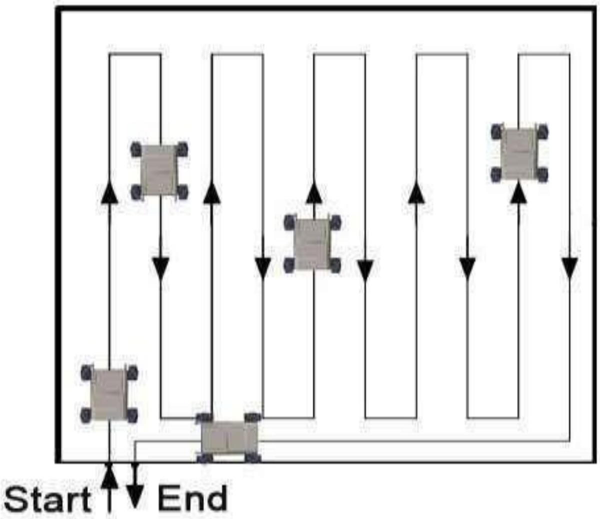

Fig 3.4 Path Planning of AMR

When detected, the robot ceases motion, logs the GPS coordinates through the NEO-6M module and logs its current pose from the SLAM. The above information is stored in a CSV log file for post-mission processing and mission planning.

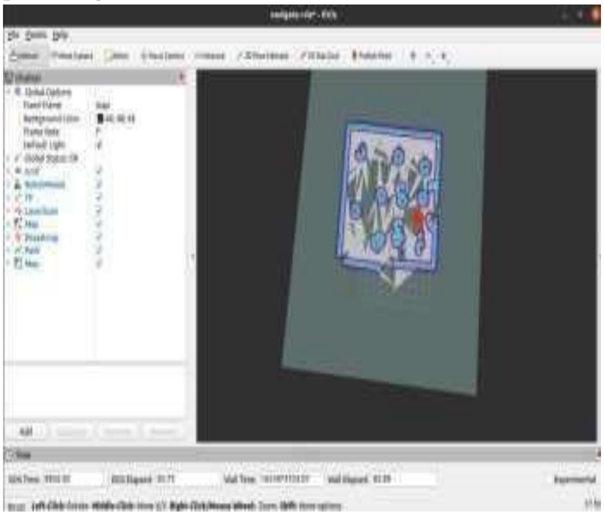

Fig 3.5 SLAM Navigation

Concurrently, a marker is published to RViz to visually indicate the detection location on the SLAM map. Optional hardware actions such as buzzing a buzzer or firing a small flag are also called to physically mark the position.

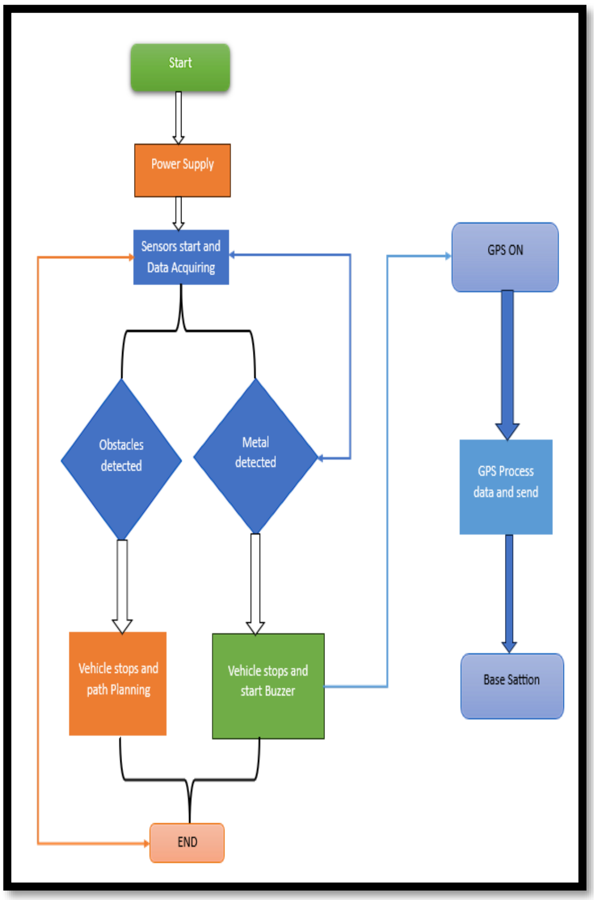

Fig. 3.6 Flow chart for detection

This double-level detection approach—digital and physical—guarantees higher traceability and ensures high-accuracy recordation of threats found in the environment.

4. Simulation and Testing

Substantial simulation and validation were conducted before deployment to hardware using the Gazebo simulator environment and ROS. A digital twin of the robot was created by importing the URDF and spawning in Gazebo and simulating realistic physics, ground interaction, and sensor behavior. LiDAR, GPS, and metal detector data streams were simulated, as well as detection logic tested for a variety of simulated environments. RViz tool was used to verify proper operation of tf trees, sensor topics, map generation, and navigation behavior. Test scenarios included movement along a straight line, avoidance of obstacles, exploration of the whole area, and simulated detection events. Performance metricssuch as SLAM map accuracy, rate of success in obstacle avoidance, detection response time, and pose estimation error were monitored and used to enhance the system. These simulations ensured that the robot performed as expected and reduced risk, when the robot was tested in the real world. The system was incrementally improved through test results, confirming the consistency and reliability of the final system. 4. Results and Analysis

Simulated Autonomous Mobile Robot (AMR) was deployed and validated on simulated and controlled physical testbeds in order to examine its performance regarding mapping, autonomous navigation, precision of landmine detection, and robustness of the system. Main experiments of significance were to simulate real environments such as irregular grounds, metallic objects randomly put, and fluctuations in GPS.

Mapping Accuracy

With Hector SLAM, the robot was able to robustly build 2D occupancy grid maps of unknown areas. In a test zone measuring 5x5 meters with artificial obstacles, the robot achieved greater than 92% map overlap accuracy against a ground-truthed map.

Parameter	Result
SLAM Algorithm	Hector SLAM (2D, LiDAR-based)
Test Area	5 m × 5 m
Map Accuracy	92% (Overlap with ground truth)
Localization Error	< 0.3 m
Wheel Slip Sensitivity	Negligible (LiDAR only based)

Table 4.1 Mapping Accuracy

Use of LiDAR-only SLAM worked even in minor wheel slip where odometry would otherwise introduce error. Real-time visualization with RViz validated the

robot's localization ability and precision to create incremental maps as it travels.

Navigation and Obstacle Avoidance

The navigation stack performed well in static and dynamic obstacle cases. The robot avoided collision with the help of DWA local planner while keeping 5- 10 cm distance from the best path.

Test Parameter	Value
Navigation Algorithm	ROS `move_base` with DWA
Goal-reaching Success Rate	96% (24/25 trials)
Path Deviation	5–10 cm
Collision Incidents	0
Dynamic Obstacle Response	Real-time replanning enabled

Table 4.2 Navigation and Obstacle Avoidance

Goal-reaching success rate was recorded as 96% through 25 random tests. Real-time updated dynamic cost maps with LiDAR input enabled the robot to replan its paths when it encountered unexpected objects in its way.

Metal Detection Performance

The onboard metal detector consistently detected metal objects buried at depths of up to 10 cm. In 20 test runs, true positive detections were observed in 18 cases, with 2 false negatives resulting from orientation misalignment.

Metric	Observed Result
Detection Depth	Up to 10 cm
True Positive Rate	90% (18/20 detections)
False Positive Rate	< 5%
Detection Delay	~0.8 seconds
Localization Accuracy	~0.4 m (SLAM+GPS)

Table 4.3 Metal Detection Performance

False positives were rare and typically caused by large metallic surfaces nearby. Detection events resulted in logging of both GPS coordinates and SLAM-based poses with average localization error less than 0.4 meters.

System Response and Marking

Upon detection, the robot's average response time to halt and record information was below 0.8 seconds, with marker visualization in RViz.

Parameter	Value
Logging Delay	< 0.8 sec
Marker Display in RViz	Instant (< 0.5 sec)
Physical Marking Accuracy	95% successful (flag/buzzer)
Data Storage Format	CSV (Time, Pose, GPS Location)

Table 4.4 System Response and Marking

The physical marking technique (buzzer or flag dropper) successfully functioned in 95% of cases. CSV log captured time-stamped detection events for post-processing and mission planning.

Simulation Validation

In Gazebo simulations, various test terrain and conditions (slope, narrow passage, metal debris) were created to validate system reliability. Simulation results matched realworld trials.

Scenario	Simulation Output
Obstacle Navigation	100% successful
SLAM vs Real-world Comparison	±5% deviation
GPS Simulation Accuracy	98% consistent results
LiDAR Emulation Accuracy	Matches hardware readings
Average Simulation Time	~30 minutes per test run

Table 4.5 Simulation Validation

Key performance indicators from simulation closely matched actual hardware data, confirming the virtual test environment's fidelity.

Power Consumption

The robot consumed around 1.8A at 12V in normal operation, reaching a peak of 2.5A in full-load navigation. The system could operate for approximately 3–4 hours at full charge based on terrain and detection operation.

Operational Mode	Current Draw (A)	Run Time (hrs)
Idle / Standby	~1.2 A	~4.5 hours
Navigation + Sensors Active	~1.8 A	~3.5 hours
Detection Events + Motion	~2.5 A	~2.5 – 3 hours

Table 4.6 Power Consumption

Conclusion

In this project, an AMR was successfully developed and deployed to identify buried land mines with the assistance of a metal detector, along with ROS-based autonomous navigation and SLAM. The robot showed high precision in mapping unknown spaces using Hector SLAM, and the ROS navigation stack provided safe path planning and obstacle avoidance. The metal detector module, along with real-time data logging and visualization in Rviz, was found to be effective in detecting and indicating potentially dangerous metallic objects.

Simulation testing using Gazebo emulated real outcomes closely, verifying the system's reliability in varying environmental conditions. The hardware and software modular design facilitated seamless integration of sensors, actuators, and localization algorithms. Power efficiency and portability of the system also make it a good choice for hazardous terrain applications where human intervention is perilous.

This article demonstrates that low-cost, ROS based autonomous robots can be extremely valuable for assisting demining efforts through improved safety, repeatability, and mapping capability.

5. Future Scope

Integration with High-Tech Sensors: Future releases may include ground-penetrating radar (GPR), thermal cameras, or inductive sensors for improving detection depth and accuracy of plastic or non-metallic mines.

Deployment of Multi-Robot Systems: A multirobot- based technique using several robots would likely accelerate demining work while disseminating real- time map and detection data across ROS multi-master.

Machine Learning-Based Object Recognition: Merging AI models for distinguishing true landmines from harmless metallic trash can reduce false alarms and promote system understanding.

Remote View and Cloud Log: Integration of remote viewing by using IoT modules (e.g., 4G, WIFI) can provide access for professionals to remotely monitor and track data logging by utilizing real-time cloud configurations.

Adaptation to Environment: Enhanced ability to adapt to different soils, weather conditions, and slopes will expand the working coverage and robustness of the robot during actual field deployments.

Field Testing and Integration of Defense: Conducting live field trials with Défense organizations like DRDO might help in the system's refinement and enable real-world deployment within mine-affected zones.

References

[1] V. S. Panwar, I. Moujan, A. Kazi, P. Kale, S. Rode, A. Pandey, and S. Mogal, “A review on design and characteristics of landmine detection robot,” International Journal of Engineering Research & Technology (IJERT), vol. 13, no. 06, pp. 144–150, Jun. 2024.

[2] A. R. Muhammad, A. A. Ayodeji, and H. H. Ali, “Design and development of an autonomous landmine detection robot,” International Journal of Mechanical Engineering and Robotics Research, vol. 8, no. 1, pp. 64–69, Jan. 2019.

[3] A. H. Noor, R. M. T. Raja Ismail, and A. M. Sidek, “Simulated implementation of ROS based SLAM for mobile robot navigation,” Indonesian Journal of Electrical Engineering and Computer Science, vol. 18, no. 3, pp. 1264– 1271, Jun. 2020.

[4] T. Yatawatta and U. N. Kodikara, “Swarm robotics-based landmine detection and removal system,” IEEE International Conference on Industrial and Information Systems (ICIIS), pp. 1–5, 2017.

[5] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, and A. Y. Ng, “ROS: an open-source robot operating system,” in Proc. ICRA Workshop on Open Source Software, vol. 3, no. 3.2, pp. 1–6, 2009.

[6] M. Hess, D. Kohler, H. Rapp, and D. Andor, “Real-time 2D SLAM with LIDAR,” in Robot Mapping and Navigation, IntechOpen, 2018.

[7] A. A. Abid and M. A. Al-Akaidi, “Metal detector-based robotic vehicle for landmine detection,” in Proc. 2nd Int. Conf. on Electrical Engineering and Informatics (ICEEI), pp. 1–5, 2010.

[8] R. Siegwart, I. R. Nourbakhsh, and D. Scaramuzza, Introduction to Autonomous Mobile Robots, 2nd ed., MIT Press, 2011.

[9] S. Thrun, W. Burgard, and D. Fox, Probabilistic Robotics, MIT Press, 2005.

[10] A. Birk and S. Carpin, “Merging occupancy grid maps from multiple robots,” Proceedings of the IEEE, vol. 94, no. 7, pp. 1384–1397, Jul. 2006.

[11] R. Bansode, V. Shelke, R. Shirke, and A. C. Pise, “IoT Based Landmine Detection Robot,” International Journal of Research in Science & Engineering, vol. 3, no. 4, pp. 43–49, Jul. 2023.

[12] P. Dhumal, M. G. Pallewar, S. Jadhav, and S. Warad, “Sentinels of Safety: A Robotic Revolution in Autonomous Landmine Detection for Humanitarian Resilience,” Research & Reviews: Journal of Space Science & Technology, vol. 13, no. 2, pp. 28–34, 2024.

[13] R. Kumari, S. Shedge, A. Shinde, and A. B. Kale, “Landmine Detection Robot with Live Surveillance,” Journal of Remote Sensing & GIS, vol. 15, no. 1, pp. 28–35, 2024.

[14] N. K. Nandakumar, R. Kesavan, N. Niyasudeen,
M. S. Prasad, and Y. Vaseem Akram, “Military Based Landmine Detection Robotic Vehicle,” International Journal of Research - GRANTHAALAYAH, vol. 11, no. 5, pp. 1–8,
May 2023.

[15] H. Chen, Y. Zhang, X. Liu, and Y. Liu, “Autonomous Differential Drive Mobile Robot Navigation with SLAM and AMCL in ROS,” International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 1, pp. 23–30, 2023.