AMR Test Platform: Intelligent Obstacle Detection and Braking via Radar-Vision Fusion

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Abstract: Autonomous Mobile Robots (AMRs) are increasingly deployed in dynamic environments where real-time obstacle detection and collision avoidance are critical for operational safety. This paper presents the design and development of an AMR Test Platform equipped with an intelligent Obstacle Detection and Emergency Braking System that fuses data from radar and vision sensors. The proposed system leverages the robustness of radar sensing and the spatial richness of visual data to achieve accurate and reliable obstacle detection. A real-time processing pipeline integrates radar signal processing, computer vision-based object detection, and a decision-level sensor fusion framework to assess potential collision threats. Upon detection, an emergency braking mechanism is triggered based on safety thresholds such as time-to-collision and object proximity. The platform was tested under various conditions involving both static and dynamic obstacles. Experimental results demonstrate improved detection accuracy, reduced false positives, and timely braking response, validating the effectiveness of the fusion approach in enhancing AMR safety. This work contributes a modular, scalable solution suitable for deployment in industrial and service robotics environments.

Keywords: Autonomous Mobile Robots, Obstacle Detection, Emergency Braking, Radar-Vision Fusion, Real-Time Processing.

I. INTRODUCTION

Autonomous Mobile Robots (AMRs) have become integral to a wide range of industries, including warehousing, manufacturing, healthcare, and last-mile delivery. Their ability to navigate complex and dynamic environments autonomously has unlocked significant gains in productivity and operational efficiency. However, ensuring the safety and reliability of AMRs, particularly in environments where they coexist with humans and other moving agents, remains a critical challenge. One of the most vital safety components in AMRs is the ability to detect obstacles in real time and initiate emergency braking to prevent collisions.

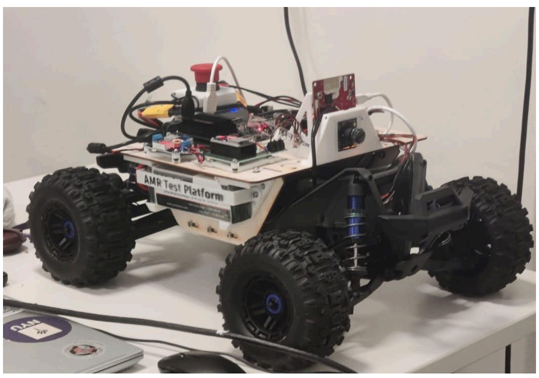

Fig 1:Prototype

Traditional obstacle detection systems often rely on single-sensor modalities such as LiDAR, ultrasonic sensors, or monocular vision. While effective in certain contexts, these solutions tend to suffer from limitations such as poor performance in adverse weather, limited range, or high computational cost. Radar sensors, on the other hand, offer robustness in various environmental conditions and are well-suited for detecting metallic and non-metallic objects at longer ranges. When combined with vision-based systems that provide rich spatial and contextual information, sensor fusion can significantly enhance the reliability and responsiveness of AMR obstacle detection systems.

In this paper, we present an AMR Test Platform equipped with an intelligent obstacle detection and emergency braking system that integrates radar and vision sensing with a real-time processing framework. Our objective is to investigate how multi-sensor fusion can improve the performance of critical safety systems in AMRs. The platform includes a custom-built obstacle detection pipeline, a sensor fusion algorithm, and a braking decision module based on time-to-collision and proximity thresholds.

The key contributions of this work are as follows:

- Development of a modular AMR test platform with integrated radar and vision sensors.
- Design of a real-time processing pipeline for obstacle detection and emergency braking.
- Implementation of a decision-level sensor fusion framework to improve detection reliability.
- Experimental evaluation of system performance in static and dynamic obstacle scenarios.

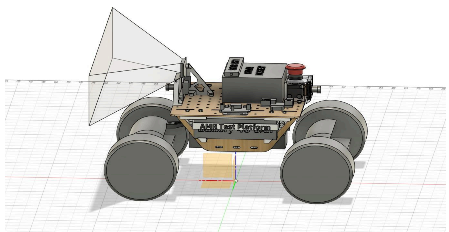

Fig 2:Mechanical design

II. RELATED WORK(Literature Review)

A. Obstacle Detection in AMRs

Overview of existing approaches (LiDAR, ultrasonic, vision, radar).Strengths and weaknesses of each.Previous work in academic/industrial settings. Focus on safety-critical application

B. Sensor Fusion Techniques

Review of sensor fusion strategies (e.g., Kalman filter, complementary filter). Real-time challenges in fusion. Comparative effectiveness of radar + vision vs others.

C. Emergency Braking Systems in Robotics

Studies on braking mechanisms in mobile robots. Metrics like braking distance, latency. Safety regulations and industrial relevance

III. SYSTEM DESIGN AND ARCHITECTURE

A. Hardware Components Overview

The hardware platform for this project is built upon a modified 4WD RC car chassis capable of achieving speeds up to 60 mph, providing a high-dynamic testbed for real-time obstacle detection and emergency braking. A compact yet powerful mini PC serves as the central computing unit, handling sensor data processing, decision-making, and communication over the Robot Operating System (ROS) framework.

The platform integrates multiple sensors and microcontrollers to enable autonomous behavior. Two cameras are mounted at the front and back of the vehicle to capture visual data for object detection. A forward-facing radar sensor is used to provide robust obstacle detection under varying environmental conditions.

Two ESP32 microcontrollers are incorporated, each assigned distinct roles. The first ESP32, referred to as ESP-Drive, interfaces with an Xbox controller and is responsible for manual driving operations. It uses micro-ROS to publish throttle and steering commands to the ROS network and subscribes to a braking topic generated by the main system, enabling autonomous or manual override braking control.

The second ESP32 is dedicated to data acquisition from an IMU and GPS module. It also employs micro-ROS to publish sensor data, allowing real-time vehicle state estimation and localization. This distributed hardware configuration ensures modularity, low-latency communication, and seamless integration within the ROS ecosystem, enabling efficient coordination between perception, decision-making, and actuation subsystems.

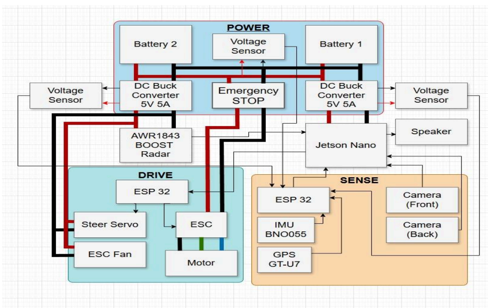

Fig 3:System architecture

B. Sensor Configuration (Radar + Vision)

The AMR Test Platform integrates a USB camera and a mmWave radar sensor to enable robust, real-time obstacle detection. These complementary sensors enhance environmental awareness by combining rich visual information with reliable range and velocity data.

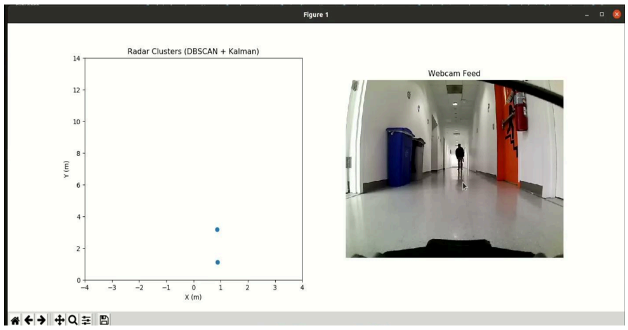

Fig 4:Sensor fusion Real-time view

Vision Sensor: A USB camera with a 5MP OV5648 CMOS sensor is used for visual detection. It features a 95° horizontal FoV M12 lens with an IR-cut filter for sharp and color-accurate images. The camera supports 640×480 resolution at 30 fps and is UVC-compliant, allowing easy integration with PCs and Raspberry Pi without additional drivers.

Radar Sensor: The radar module is the TI AWR1843 BoosterPack, a 77 GHz mmWave sensor with an onboard antenna. It integrates a C67x DSP and ARM R4F core for real-time signal processing and connects via UART-to-USB. Compatible with TI LaunchPad kits, it enables rapid prototyping. Optional extensions like the DCA1000EVM allow raw data access for advanced development.

This sensor setup combines the spatial detail of vision with the environmental robustness of radar, forming the backbone of the AMR's real-time obstacle detection and emergency braking system.

C. Processing Unit and Software Stack

The proposed system utilizes a hybrid processing architecture comprising an ESP32 microcontroller and a Mini PC to coordinate sensor input and control logic. The Mini PC operates on a lightweight, Linux-based operating system selected for its support of real-time performance and low-latency task execution.

The software stack integrates several widely adopted frameworks. The Robot Operating System (ROS) serves as the middleware for modular communication between sensor nodes and control modules. OpenCV is employed for real-time computer vision tasks, including image acquisition, preprocessing, and object detection. PyTorch is used for implementing machine learning models aimed at obstacle classification and behavior prediction.

The end-to-end data flow is structured into four sequential stages: (1) sensor data acquisition, encompassing radar and camera inputs; (2) data processing, involving fusion of multimodal sensor data; (3) decision-making, where obstacle presence and severity are evaluated to generate safe responses; and (4) actuation, in which the appropriate control signal (e.g., braking or evasive maneuver) is executed.

D. AMR Braking Mechanism Integration

The braking mechanism in the AMR test platform is designed to leverage the existing motor controller behavior for rapid and effective stopping. The Electric Speed Controller (ESC) manages braking by reversing the motor signal direction at maximum power, effectively jamming the motor shaft and subsequently locking the gear assembly. This action results in all four wheels being immobilized, providing a robust braking response when the AMR is moving forward.

The ESC is interfaced with both the Mini PC and an Xbox controller, enabling multiple control pathways for braking. The Xbox controller features two distinct braking modes:

- **Normal Brake:** This mode commands the ESC to apply braking force without altering the current driving mode. It is typically used for temporary halts where the AMR may need to resume movement shortly after.
- **Reset Brake:** In this mode, the braking action is combined with a shift into "neutral." Once engaged, the AMR remains immobilized until an explicit command is given to switch back to "drive" mode, adding a layer of safety during critical stop conditions.

Additionally, the system supports a software-based braking interface through a ROS topic named "/brake_input", which is published by the Mini PC. This enables the AMR to respond to autonomous decisions made by onboard perception and planning algorithms, ensuring seamless integration with real-time obstacle detection and emergency stop commands.

This multi-modal braking architecture enhances both manual control flexibility and autonomous safety, allowing the AMR to operate reliably in dynamic environments.

IV. METHODOLOGY

A. Obstacle Detection Pipeline

System pipeline diagram. Flow of sensor data to detection and braking within FOV of ±40°.

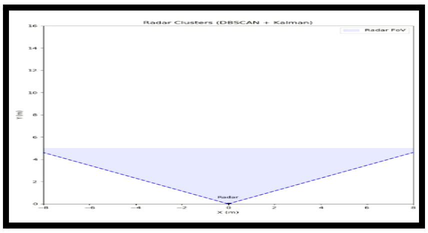

Fig 5:Radar FOV

B. Radar Clustering and Tracking

DBSCAN is used to group radar points corresponding to potential objects based on spatial proximity and density. A Kalman Filter is applied to track detected objects across frames, smoothing noise and predicting motion trajectories.

C. Vision-Based Object Detection

Detection algorithm (e.g., YOLO v8). Real-time image processing: resizing, ROI selection. Tracking across frames.

D. Sensor Fusion Algorithm

Camera Calibration : **Intrinsic Parameters -** Focal length, principal point, distortion coefficients. **Extrinsic Parameters-** Rotation and translation matrices mapping camera frame to vehicle frame

E. Real-Time Decision Framework

Braking threshold logic (e.g., time-to-collision, distance). Multi-threading or real-time scheduling. Latency optimization techniques.

V. EXPERIMENTAL SETUP

A. Test Environment and Conditions

To evaluate the performance of the obstacle detection and emergency braking system, experiments were conducted in three distinct environments designed to simulate real-world use cases with varying complexity.

The first environment was a small indoor room used for initial static tests. In these trials, the AMR remained stationary while a controlled obstacle moved within the field of view to test the system's ability to detect approaching objects. This setup enabled precise assessment of the radar and vision system's detection sensitivity and responsiveness under controlled lighting and background conditions.

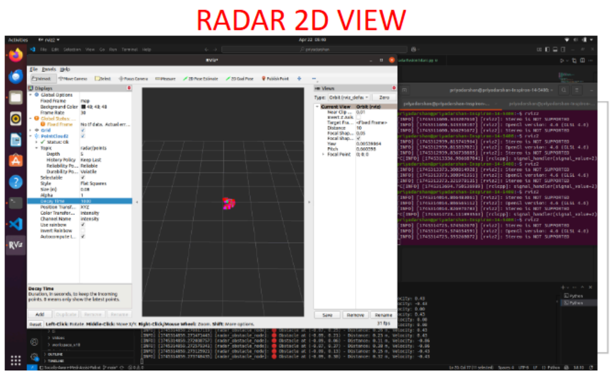

Fig 6:Radar 2D view after filter

The second environment was a long, narrow corridor, chosen to test both the radar's effective sensing range and the braking performance of the AMR in a straight-line path. Two key experiments were performed: one to measure maximum obstacle detection distance with the AMR stationary, and another where the AMR moved toward a static obstacle to evaluate the full emergency braking pipeline in a constrained environment.

The third environment involved outdoor testing at dawn, introducing variability in lighting, obstacle types, and surface conditions. This scenario focused on dynamic obstacle interaction, including static objects, frontal intrusions (obstacles entering from the front), and overtaking maneuvers where obstacles crossed the AMR's path laterally. The AMR was tested at multiple speeds to evaluate system robustness under real-world uncertainty and environmental noise.

B. Test Scenarios (Static, Dynamic Obstacles)

The test scenarios were divided into three categories:

- Static Scenario: Stationary AMR with moving obstacle to test sensor field coverage and false positive filtering.
- Straight-Line Motion Scenario: AMR moving toward a static obstacle to assess braking timing and detection latency.
- Dynamic Obstacle Scenario: AMR navigating while dynamic obstacles approached from the front or side, simulating real-world human or object movement patterns.

Each scenario was repeated under different conditions (e.g., lighting, obstacle type, and speed) to ensure generalizability.

C. Evaluation Metrics

System performance was assessed using the following key metrics:

- **Braking Response Time:** Time elapsed from obstacle detection to braking signal activation.
- **Braking Distance:** Distance traveled from the time of detection to full stop.
- **False Positive/Negative Rate:** To evaluate the reliability of the detection system in complex scenarios.
- **System Latency:** Total delay from sensor input to actuation command.

These metrics provided a comprehensive view of the system's real-time effectiveness and safety-critical performance.

VI. Results and Discussion

A. Obstacle Detection Accuracy

Confusion matrix (for vision/radar individually and combined). Precision, recall, F1-score.

B. Braking Response Time

Time from detection to braking signal. Time from braking signal to full stop. Comparison across sensors and fusion.

C. Failure Cases and Analysis

While the proposed radar-vision fusion system performed reliably in most test scenarios, a few noteworthy failure cases emerged during experimentation. The most prominent issue was the system's sensitivity to lighting conditions, particularly affecting the vision-based detection module. Specifically, the algorithm consistently detected obstacles with high accuracy under white light illumination but showed reduced performance under warm light environments. This degradation in accuracy was not reported in other related works, indicating a potential gap in current literature regarding color temperature sensitivity in visual perception pipelines.

No other consistent failures were observed; however, an important behavioral trend was noted in the mmWave radar module. The radar's output varied significantly across different indoor and semi-structured environments, potentially due to reflections, multipath effects, or environmental clutter. These variations did not lead to complete detection failures but did affect confidence levels and spatial accuracy, highlighting the need for environment-aware radar calibration or adaptive filtering in future iterations.

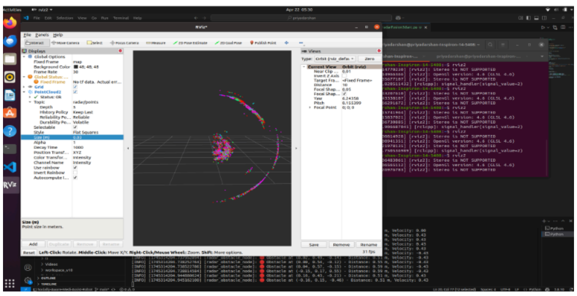

Fig 7: Radar Noise data 3D-View

Overall, while the system showed strong generalizability, these observations emphasize the importance of robust vision models under varying lighting conditions and further characterization of radar behavior across deployment contexts.

VII. Conclusion and Future Work

A. Summary of Findings

Highlight key contributions: fusion efficiency, braking accuracy, platform reliability. Validation through experiments.

B. Future Directions

While the proposed system demonstrates effective obstacle detection and emergency braking using radar-vision fusion, several enhancements can further improve performance and scalability. First, the integration of additional sensing modalities such as LiDAR or IMUs can provide richer spatial awareness and redundancy, especially in cluttered or low-visibility environments. Second, incorporating machine learning techniques for adaptive sensor fusion and context-aware decision-making could enhance the system's robustness to varying obstacle types and motion patterns.

Future work will also focus on optimizing computational efficiency to support deployment on resource-constrained edge devices without compromising real-time performance. Expanding the test platform to operate in outdoor or industrial settings will help evaluate system reliability under more diverse conditions. Lastly, integrating this safety system into a fleet of AMRs and enabling cooperative braking or communication via V2X protocols presents an exciting opportunity for coordinated navigation in multi-robot environments.

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