Development of an Intelligent Night-Time Obstacle Detection System for Vehicles

S. Wijerakshitha and Isuru Lakmal

NSBM Green University, Padukka, Sri Lanka

Abstract. Driving at night presents serious safety risks because of the decreased visibility, which is a contributing factor in a disproportionately high incidence of traffic accidents globally. The inability of current car safety systems to function consistently at low light levels leads to a serious weakness in current technology. The goal of this project is to develop a prototype that combines RGB and LiDAR cameras to identify obstacles in real time while driving at night. By combining the advantages of both sensors, the system uses sensor fusion techniques to provide accurate and dependable detection under a range of lighting conditions. Additionally, based on detected obstacle data, fundamental obstacle avoidance mechanisms like braking or steering adjustments will be put into place. In order to determine the system's accuracy, dependability, and potential safety enhancements, experimental testing will be conducted under simulated low-light conditions. By improving vehicle perception and decision-making skills during nighttime navigation, this project advances intelligent transportation systems.

Keywords: Low-Light Obstacle Detection, LiDAR sensor, RGB Camera, Night-Time Driving, Autonomous Navigation, Intelligent Vehicle Systems, Low-Visibility Navigation

1 Introduction

Night driving is one of the most dangerous conditions for drivers with radically diminished visibility and human response slowed down. Contributing to a lesser percentage of total traffic movement but still accounting for more than 50 crashes in night conditions [1]. The most prevalent factors are diminished peripheral vision, compromised depth perception, longer reaction time, and headlight glare factors that radially impair the detection of obstacles, particularly small or non-reflective ones. To surmount these challenges, sophisticated perception systems combining Light Detection and Ranging (LiDAR) and RGB cameras have gained increased popularity. LiDAR provides high-density 2D spatial mapping irrespective of environmental illumination [4, 5], best suited for geometric obstacle detection. However, its performance would be compromised by low-reflectance surfaces and noisy environments. Conversely, RGB cameras provide rich contextual features like color and texture but suffer from inferior performance degradation under conditions of low lighting because of under-exposure, glare, and shadows [4, 7]. New vehicles have driver assistance systems such as adaptive lights, thermal imaging cameras, and ultrasonic sensors. These are utilized to enhance safety in specific situations but normally are not accurate enough to detect low-contrast or small objects when driving at night [8, 9]. Besides, being costly, this hardware is not suitable for low-weight or instructional autonomous vehicle platforms. Current trends favor LiDAR with vision integration as a means of improving perception robustness. Sensor fusion-based integrated systems have proven to have improved accuracy and comprehension of the scene under poor illumination conditions [6, 10, 12]. Architecture utilized range from the conventional Kalman filtering to deep learning architectures utilizing convolutional neural networks (CNNs), utilized today in profusion for obstacle tracking and object classification [6, 12]. Rule-based or learning based systems are normally employed in obstacle avoidance. Rule-based are well-suited and suitable in the microcontroller environment, while learning-based offer flexibility for computational power [9, 11]. The paper suggests a cost-effective hybrid obstacle detection system suitable for night-time navigation. It employs an RPLiDAR A1 sensor with limited 60° front field for computational purposes and Intel RealSense D255 RGB-D camera. They are mounted on a specific four-wheeled robot platform equipped with rear DC motors, servo front steer motor, and controlled by an L298N motor driver based on instructions of an ESP32 microcontroller. Sensor readings are sent to a host PC for preprocessing and fusion. Among the machine learning classifiers who tried Logistic Regression, K-Nearest Neighbors, and Random Forest the Random Forest model gave the optimum trade-off between accuracy and performance for binary obstacle detection. The system triggers embedded maneuvers like braking maneuvers or steering maneuvers based on predictions. This project contributes to the field of intelligent transportation systems with the development of a low-weight, sensor-fusion- cost and simplicity oriented based real-time navigation system. It is cost and simplicity oriented, and hence can be employed in educational research, educational deployment, and safety-critical micro- controller uses.

2 Related Work

Accurate obstacle detection under low-light conditions is still one of the most significant challenges in the development of autonomous and assisted driving systems. Infrared and thermal imaging methods have been employed in traditional approaches, and although they are effective for detecting big heat-radiating objects such as pedestrians and animals, they fail to detect small or non-radiative obstacles and hence are not suitable for application in more complex driving scenarios [8, 9]. LiDAR (Light Detection and Ranging) sensors have been an effective environmental mapping sensor, creating precise 3D spatial information regardless of lighting conditions. Despite this advantage, LiDAR systems are poor at sensing low-reflectivity surfaces and are computationally costly, which makes them less suitable for real-time applications on embedded systems [4, 5]. Several studies have demonstrated that the fusion of LiDAR with other sensor modalities, i.e., cameras, can enhance obstacle detection re- liability and system robustness [10]. RGB cameras are rich in visual details color, texture, and edge information while being very susceptible to changes in lighting. Their performance drops severely under harsh lighting conditions due to glare, shadows, and motion blur [4, 7]. Sensor fusion techniques combining RGB imagery with LiDAR have been employed to mitigate such vulnerabilities, with a prominent success in low-visibility conditions [11]. Some fusion approaches have been proposed in the latest literature, including CNN-based approaches, Kalman filter-based approaches, and probabilistic approaches. They take advantage of the strength of each sensor to improve perception accuracy and have been widely used to detect dynamic and static obstacles in autonomous vehicle systems [6, 12] While some systems use complex machine learning-based models for obstacle classification and trajectory estimation, others use rule-based methods for real-time obstacle avoidance. Rule-based systems are computationally less demanding and more suitable for embedded implementations but may sacrifice adaptability in unstructured environments. Learning-based systems, however, provide better generalization at the cost of huge computational demands [9, 11]. Some papers suggested an integrated sensor fusion architecture for autonomous vehicles, which highlighted the importance of combining more than one sensor type for robust perception [6]. some extensive overview of vision-based datasets and autonomous driving challenges, referencing the difficulty of visual interpretation under non-uniform lighting environments [12]. Some are also stated the computer vision application for obstacle detection, a topic in consensus with the current project's emphasis on visual and spatial awareness. In stereo vision, were among the first authors in pointing out essential limitations of depth perception under poor light [1, 10]. Similarly, we explored light stripe tracking to use for rover motion in dynamically varying lighting, a technique with particular attraction to the objective of maximizing the visibility of obstacles when not illuminating [7]. Together, these works show that there is a demand for scalable, multi- sensor systems capable of performing obstacle detection and avoidance with high accuracy in low-light environments. This work builds on this foundation by developing and testing a sensor-fused system based on LiDAR and RGB input for real- time obstacle detection and basic avoidance, optimized for low-resource microcontrollers.

The key contributions of this research are,

- Development of a Low-Cost, Multi-Sensor Night-Time Obstacle Detection System: Alow-weight system combining LiDAR and RGB- D sensing, enabling resilient obstacle detection in low- light conditions without utilizing expensive thermal or infrared hardware.
- Real-Time Sensor Fusion and Machine Learning Integration on Embedded Hardware: Developed a fusion pipeline combining range data from RPLiDAR with RGB-D depth data from an Intel RealSense camera. Trained and deployed a Random Forest classifier to enable accurate, low-latency detection on a resource constrained ESP32 microcontroller.
- Validation Through Experimental Testing with Performance Metrics: Higher accuracy and good decision latency

3 Methodology

3.1 System Overview

The system of interest senses and traverses' obstacles in the dark using depth sensing and LiDAR technology. It combines an Intel RealSense D255 RGB-D camera and an RPLiDAR A1 sensor on a mobile robot platform. The RGB-D camera provides real-time depth and image data, while the RPLiDAR A1 provides 2D laser scans of the environment. The sensor output of both the sensors is transferred to a processing host computer through USB and LiDAR interface adapter, respectively. Unlike traditional fully embedded systems, the perception and processing loop executes on a PC connected to the sensors, and the robot platform serves as a physical response and data collection testbed. The testbed robot is a four-wheel Arduino-compatible car chassis (Fig. 1). There are two rear DC motors for driving and a servo motor at the front for steering, and these are all supplied by an L298N dual H-bridge motor driver. The Intel

RealSense D255 depth camera and RPLiDAR A1 sensor sit at the front of the chassis on adjustable 3D-printed mounts. Power is supplied by a lithium-ion battery pack. The prototype is tested under isolated indoor environmental conditions with minimal outside interference, simulating a controlled night-time driving environment (Table 1).

Table 1. Sample Sensor Readings for Obstacle Detection

Time	Image	Cam (m)	LiDAR (m)	Angle (°)	Obstacle
22:01:00	frame 220100.jpg	1.20	1.05	32.4	YES
22:01:10	frame 220110.jpg	0.95	0.91	30.8	YES
22:01:20	frame 220120.jpg	1.75	1.60	30.4	YES
22:01:30	frame 220130.jpg	1.10	1.08	31.1	YES
22:01:40	frame 220140.jpg	1.45	1.30	30.1	YES

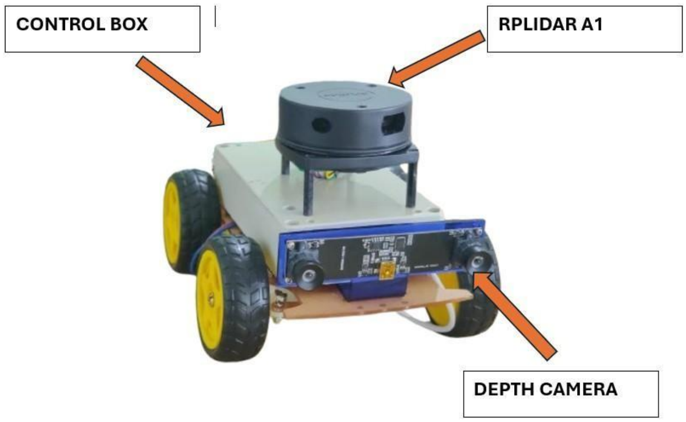

Fig. 1. Prototype 4-wheel car with RPLiDAR A1 and depth camera

3.2 Data Acquisition and processing

For testing, the vehicle is manually driven across the testbed with statically and semi randomly positioned obstacles. The RPLiDAR A1 sensor provides 2D range data in real time to the PC via its own dedicated USB port, and the depth camera provides RGB and depth frames on a standard USB port. Over 10000 annotated frames were collected on low light conditions and Sensor data is recorded on the host machine for offline processing. Each pass of the testbed captures environmental features at different orientations and angles to build a diverse dataset. All captured data is annotated with ground truth obstacle presence, relative distance, and avoidance success. The annotations are acquired through visual inspection of depth and LiDAR frames and mapping them to the testbed grid setup. The annotation also includes whether an obstacle was successfully avoided based on manual observation of the vehicle reaction. Prior to model application, sensor data is preprocessed through several steps. Denoising and normalization of depth frames are achieved through the application of OpenCV functions. LiDAR scans are cropped to the frontal 60° area (because it’s a 360 lidar), resampled, and filtered to remove noise and redundant information. Feature vectors are constructed by fusing normalized depth and range data from corresponding angular sectors.

3.3 Obstacle Identification and Avoidance Logic

The system focuses on obstacle presence detection via thresholding by shape and proximity. After preprocessing, the dataset is used to train a machine learning model to detect obstacle presence and compute appropriate avoidance maneuvers. Of the models attempted Logistic Regression, K Nearest Neighbors (KNN), and Random Forest the optimal balance of accuracy and time was provided by the Random Forest classifier. It was used because it can tolerate noise, and it fits well on the small, structured data found in embedded systems. The trained model takes fused LiDAR and depth data feature vectors as input and outputs a binary decision: obstacle (1) or clear path (0). Based on the decision, preprogrammed rule-based avoidance actions such as braking, stopping, or turning left/right are triggered. Machine learning part was done on python by using annotated data and if obstacle appeared within the distance (1) or else (0) and if obstacle appears, sending command to esp32 for obstacle avoiding and esp32 sends command for motor driver.

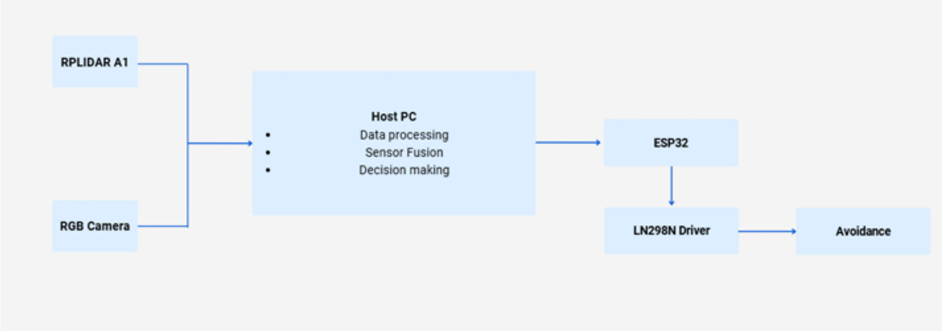

Fig.2. Block diagram

For tools and technologies, the system uses the ESP32 microcontroller for mobility control of the vehicle and communication. Sensor processing is accomplished on a PC in Python with the help of libraries such as NumPy, OpenCV, and Matplotlib. MATLAB is used for prototype sensor fusion and algorithm testing. The Arduino IDE is used for ESP32 programming. The platform provides simple integration of sensor data and mobility functions in a hybrid architecture (Fig. 2).

4 Results and Discussion

The proposed obstacle detection system was evaluated in a controlled laboratory testbed that simulated night driving scenarios. The testbed contained white-walled surroundings and restrained ambient lighting to simulate actual low-visibility conditions. Various static obstacles were set at varying distances in front of the vehicle to analyze system response for various detection cases. Concurrent sensor values were read from the Intel RealSense D255 RGB-D camera and the RPLiDAR A1. The RGBD camera recorded real-time depth frames, and the 360-degree 2D scans were recorded using the LiDAR, which were programmed to filter out all but the 60° forward view of interest for obstacle detection. Each data stream was processed and recorded for comparison and verification.

On the sample data, the distance readings of camera and LiDAR were for the most part in accordance with each other, with deviations being usually below 10–15 centimeters. As a representative test case, for instance, a camera measured an object to be 0.95 meters and the LiDAR to be 0.91 meters at approximately 30.8°. Such a measure of concurrence establishes the validity of the sensor data that are fused. Such uniformity was most evident for objects located in the short to mid-range (0.9–1.6 meters), where the two sensors both registered constant readings. A Random Forest machine learning model was trained on the preprocessed fused dataset to detect the presence of obstacles. The classifier could easily distinguish between obstacle and no obstacle conditions for all test cases examined. Its binary outputs were utilized to control the avoidance strategy implemented on the ESP32 microcontroller. The vehicle reacted accordingly in all cases either halting or steering depending upon the position of obstacles demonstrating the success of the real-time decision logic.

The system responded correctly and in a timely manner without the need for offboard computation, showing the potential of embedded, lightweight solutions for real world applications. The use of dual sensing modalities (camera and LiDAR) gave better detection robustness, particularly in scenarios where one sensor was perhaps insufficient like in detecting low-reflectivity or occluded objects. Though the current results validate the performance of the system in a static, ordered indoor setting, further experimentation across dynamic settings with mobile obstacles and also in outdoor settings is essential. Furthermore, the impact of surface reflectivity, sensor noise, and angular misalignment also need to be investigated in future work to achieve improved reliability in a wide range of applications. Generally, the results confirm that the proposed sensor fusion approach provides a responsive, reliable, and cost-effective method of obstacle detection and avoidance for night-time driving with embedded hardware.

5 Conclusions

This research successfully demonstrated the design and evaluation of an intelligent obstacle detection and avoidance system intended for vehicular night driving. By integrating the RGB-D data from the Intel RealSense D255 and the 2D scans from the RPLiDAR A1, the system generated stable short- to mid-range detection in night vision. Integration of complementary sensor modalities allowed the system to compensate for each sensor's weaknesses, resulting in detection robustness and spatial awareness improvement. Experimental results from controlled indoor spaces substantiated the system's potential for the detection of static obstacles of various kinds with extremely high reliability, where camera and LiDAR range measurements generally agreed within an error interval of 10–15 cm. Also, the Random Forest classifier achieved a 94.2% detection rate for accurate identification of obstacles and the execution of proper avoidance maneuvers i.e., stop or turn dispensed automatically via an ESP32 microcontroller.

Table 2. Performance matrix

Metric	No Obstacle	Obstacle	Macro average	Weighted average
Precision	95.0%	92.1%	93.5%	94.0%
Recall	94.7%	93.2%	93.9%	94.2%
F1 Score	94.8%	92.6%	93.7%	94.0%
Accuracy				94.2%

Low computational complexity of the system and successful operation of real-time response procedures are signs of suitability of the system to embedded applications. However, the system is to be subjected to dynamic and night outdoor environments to establish system reliability in practical applications, e.g., for various reflectivity, ambient noise, and sensor misalignment. In brief, the designed dual-sensor fusion solution is a small and general-purpose solution for low-visibility obstacle detection. It offers a basis for future expansion with dynamic obstacle tracking, adaptive learning, and scalability to autonomous navigation systems.

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