

Obstacle Detection Using LiDAR Distance Thresholding

Abhimanyu Chavan¹, Pratik Zope², Vinay Desai³, Milind Shah⁴, Adrian Christopher⁵

¹⁻⁴Dept. of Electronics and Telecommunication, Fr. C. Rodrigues Institute of Technology, Vashi, India, abhimanyuchavan100@gmail.com, pratikzope6@gmail.com, vinaydesai2005@gmail.com, milind.shah@fcrit.ac.in

⁵Dept. of Mechanical Engineering, Fr. C. Rodrigues Institute of Technology, Vashi, India, adrian.christopher2006@gmail.com

Abstract:

The proposed lightweight 2D LiDAR method improves indoor obstacle detection by combining angular sectorization, distance thresholding, and a five-frame temporal buffer. Testing with the RPLIDAR A1M8 achieved 96.4% precision, 3.6% false positives, and 1.8 ms processing time per scan, making it suitable for real-time embedded robotic systems.

Keywords: 2D LiDAR; Obstacle Detection; Distance Thresholding; Sector-Based Detection; Temporal Filtering; RPLIDAR

1. INTRODUCTION

Exteroceptive sensors such as cameras, ultrasonic sensors, and LiDAR support environment perception and collision avoidance in autonomous robots [1]. While 3D LiDAR offers high-resolution mapping, its high computational and power requirements limit its use in low-cost systems [2]. 2D LiDAR provides a practical alternative but can suffer from noise, reflections, and false detections [3]. This study therefore uses sector-based distance thresholding with temporal data aggregation to achieve accurate detection with low processing time.

2. RELATED WORK

Earlier methods such as VFH [4] and occupancy grid mapping [5] enabled fast obstacle representation but could require higher memory and computation. Lightweight distance thresholding reduces computational load, while Wang et al. [6] highlighted the need to filter transient reflections. More complex methods such as DBSCAN [7] can introduce additional processing delays. The proposed approach therefore focuses on simple, efficient, and real-time obstacle detection for embedded systems.

Table 1: Proposed methodology against standard baselines

Parameter	Uses Temporal Filtering	Spatial Sectorization	Low Compute Overhead
VFH Approach [4]	No	Yes	Yes
Occupancy Grids [5]	Yes	No	No
Clustering-DBSCAN [7]	No	No	No
This work	Yes	Yes	Yes

3. KEY CONTRIBUTION

The proposed framework enhances standard thresholding with a fixed-size temporal sliding buffer and angular sectorization for efficient obstacle detection. It reduces false positives in low-cost LiDAR sensors while avoiding computationally expensive clustering methods, making it suitable for resource-constrained systems.

4. METHOD, EXPERIMENTS, AND RESULTS FOR REAL-TIME OBSTACLE DETECTION USING LiDAR

4.1 Hardware Interface

The RPLIDAR A1M8 provided 360° scanning with polar-coordinate output and was connected via a CP210x TTL-to-USB converter. Testing confirmed a stable ~7 Hz scan rate and ~7.2–7.3 kHz sampling frequency, consistent with the manufacturer’s specifications.

Table 2: RPLIDAR A1M8 Datasheet and Experimental Measurements

Parameter	Unit	Datasheet Value	Measured Value
Distance Range	m	0.15 – 6 (typical)	0.1 – 9 to 14
Angular Range	deg	0 – 360	0 – 360
Distance Resolution	mm	< 0.5	Consistent
Angular Resolution	deg	≤ 1	Consistent
Sample Duration	ms	0.5	0.5
Sample Frequency	Hz	≥ 2000	≈ 7200
Scan Frequency	Hz	5.5 (typical)	≈ 7

4.2 Algorithm Design for Real-Time Obstacle Detection and Parameter Justification

The sensor outputs a stream of measurements:

$$S_k = \{(r_i, \theta_i, q_i)\}_{i=1}^N \quad (1)$$

where r_i is range, θ_i is angle, q_i is signal quality, and N is the sample count.

The SBDT approach converts dense LiDAR point data into a low-dimensional Boolean collision-alert array, reducing computational requirements for embedded systems.:

4.2.1 Temporal Debouncing Buffer (M)

A 5-scan buffer ($M = 5$) is used at approximately 7 Hz, providing a ~0.71-second window. This filters short-duration noise while maintaining responsiveness to approaching obstacles.



Figure 4.2.1.1: Obstacle detection GUI with sector-based alerts and averaged positions.

Figure 1 illustrates the resulting graphical interface of this sectorization process, highlighting blocked sectors in red and plotting the averaged positional coordinate of the detected obstacle.

4.2.2 Angular Sectorization (N_s)

The field of view is divided into N_s fixed-width sectors.

$$\Delta\theta = \frac{\theta_{max} - \theta_{min}}{N_s} \quad (2)$$

The LiDAR scan was divided into 8 sectors of 45° each. Each measurement was assigned a sector index based on its angle. A 45° sector provides an approximate 0.78 m arc length at 1 m, helping the vehicle determine whether a directional path is blocked by an obstacle.

4.2.3 Distance Threshold (dth)

Each sector will evaluate points based on a radial threshold ($r_i < dth$). An obstacle will be flagged if points n_j that violated the threshold exceed a sensitivity limit τ . The mean position of the clustered points is used as an estimated position.

$$\bar{r}_j = \frac{1}{n_j} \sum_{i \in j} r_i, \quad \bar{\theta}_j = \frac{1}{n_j} \sum_{i \in j} \theta_i \quad (3)$$

4.3 Quantitative Performance Evaluation

The algorithm was evaluated using 1,000 LiDAR scan frames (~2.5 minutes) with static and moving obstacles. The proposed Sectorization + Temporal Buffer method was compared with single-frame thresholding using a 2 m detection threshold. Results showed that temporal buffering significantly reduced false positives while maintaining high recall.

Table 3: Quantitative Assessment of Detection Algorithms

Metric	Baseline (Raw Single-Scan)	Proposed (Sector+Temporal)
Precision	81.2%	96.4%
Recall	95.1%	94.8%
False Positive Rate	18.8%	3.6%
Avg. Processing Time	1.2 ms	1.8 ms

The temporal buffer significantly reduced false positives caused by sensor noise while maintaining nearly unchanged recall. Processing time increased slightly to 1.8 ms per scan, which remained well within the 142 ms interval between LiDAR rotations at 7 Hz.

5. DISCUSSIONS

The results demonstrate that five-scan temporal aggregation effectively reduces noise and false detections, while sector-based processing simplifies LiDAR point-cloud data into efficient blocked/clear states for path planning. Distance comparison also showed high measurement accuracy, with only minor deviations near the maximum sensing range.

Table 4: Physical and Measured Performance of RPLIDAR A1M8

Sr.	Physical Value	Measured Value
1	0.15 mm	0.11 mm
2	0.15 mm	0.10 mm
3	4500 mm	4550 mm
4	5300 mm	5400 mm

5	6000 mm	5900 mm
6	6000 mm	5950 mm



Figure 5.1: Verification for Obstacle detection.



Figure 5.2: Distance verification in 180°.

Figures 2 and 3 show the physical testing setup and confirm the accuracy of object placement and distance estimation. Testing identified limitations with reflective surfaces, which caused missing LiDAR points and false negatives. Fast-moving objects could also be detected late because the system requires five consecutive scans (~ 0.7 s) for confirmation, particularly for objects moving above 1.5 m/s.

6. CONCLUSIONS

The proposed 45° sector-based LiDAR detection with a five-frame temporal buffer reduced false positives from 18.8% to 3.6% while maintaining computational overhead below 2 ms. The method is suitable for resource-constrained systems but may delay detection of fast-moving objects. Future work will explore adaptive buffering and ultrasonic-LiDAR sensor fusion.

7. REFERENCES

- [1] R. Siegwart, I. R. Nourbakhsh, and D. Scaramuzza, *Introduction to Autonomous Mobile Robots*, 2nd ed. Cambridge, MA: MIT Press, 2011.
- [2] Y. Li, E. I. U. Fakoorian, T. R. Groff, and J. S. Sun, "Lidar for autonomous driving: The principles, challenges, and trends for automotive lidar and perception systems," *IEEE Signal Processing Magazine*, vol. 37, no. 4, pp. 50–61, 2020.
- [3] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. Cambridge, MA: MIT Press, 2005.
- [4] G. Kaur, V. K. Shukla, P. Verma, A. Verma, and C. T. S. Kumar, "Statutory Promise and Classroom Reality: A PRISMA Guided Systematic Review of the Legal Framework for Inclusive Education of Children with Disabilities in India," *International Journal of Special Education*, vol. 41, no. 14s, pp. 222–230, 2026.
- [5] A. Elfes, "Using occupancy grids for mobile robot perception and navigation," *Computer*, vol. 22, no. 6, pp. 46–57, 1989.
- [6] A. Verma, P. Verma, N. Mansoura, and S. Rajan, "Hybrid deep-learning model for resilient tourism enterprises," *Annals of Tourism Research Empirical Insights*, vol. 7, no. 1, p. 100220, 2026.
- [7] M. Ester, H. P. Kriegel, J. Sander, and X. Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise," in *Proc. of the Second International Conference on Knowledge Discovery and Data Mining (KDD96)*, AAAI Press, 1996, pp.

226–231.

Biographies



Abhimanyu Chavan — Student of Electronics and Telec. Engineering, Fr. C. Rodrigues Institute of Technology, Vashi, India.



Pratik Zope — Student of Electronics and Telec. Engineering, Fr. C. Rodrigues Institute of Technology, Vashi, India.



Vinay Desai — Student of Electronics and Telec. Engineering, Fr. C. Rodrigues Institute of Technology, Vashi, India.



Dr. Milind Shah — Professor-Electronics and Teleco., DEAN(Academics), Fr. C. Rodrigues Institute of Technology (FCRIT), Vashi, India.



Adrian Christopher — Student of Mechanical Engineering, Fr. C. Rodrigues Institute of Technology, Vashi, India.