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Advancing Autonomous Vehicle Intelligence Through Multi-Sensor Fusion: Design, Simulation, and Performance Analysis

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Abstract: The advancement of Autonomous Vehicle technology hinges on the system's ability to perceive its surroundings accurately and make timely, intelligent decisions. One of the major challenges in autonomous navigation is achieving reliable perception in dynamic and complex environments. This paper investigates the integration and fusion of heterogeneous sensors to improve situational awareness and decision-making for autonomous vehicles. The data from multiple sensors are combined by the system which includes LiDAR, RADAR, Ultrasonic Sensors, and RGB cameras, it is observed that the data from each of the sensor is found to be complementary about the environment. LiDAR offers precise depth and 3D mapping, cameras feed the visual data in the view of object detection, radar is effective when the visibility is poor, and ultrasonic sensors support close-range obstacle detection. Through the technique of sensor fusion, the strengths of each sensor are leveraged while minimizing their individual weaknesses.

Simulation environments are developed using MATLAB, where realistic driving scenarios are created with various actors (vehicles, pedestrians, static objects) and environmental conditions. The data from the various sensors are processed through perception algorithms to perform object detection, classification, and tracking. Based on the interpreted environment, decision-making algorithms enable actions such as lane- maintenance, obstacle avoidance, and speed control.

The results demonstrate that a multi-sensor fusion approach significantly enhances the reliability, accuracy, and robustness of autonomous vehicle perception and decision-making, particularly in challenging scenarios. This work contributes to the design of safer, more intelligent self-driving systems and lays a foundation for future improvements in real-world autonomous navigation.

Keywords: Autonomous Vehicle, Muti sensor, Data fusion, perception, Decision making.

I. INTRODUCTION

The rapid evolution of Autonomous Vehicle (AV) Technology is reshaping the transportation. Self- driving vehicles are expected to significant impact is produced towards the accidents reduce road accidents caused by human error, improve traffic flow, and enhance the overall mobility experience. However, achieving full autonomy presents substantial technical challenges, particularly in the domains of environment perception and real-time decision- making. For an autonomous vehicle to navigate safely, it must continuously understand its surroundings, predict the behaviour of dynamic elements (like pedestrians and other vehicles), and make timely, context-aware driving decisions. This process requires accurate sensing, interpretation, and decision logic that work reliably under diverse environmental conditions.

Single-sensor systems (e.g., using only cameras or only LiDAR) often struggle with robustness and reliability. For instance (1) Cameras provides deep visual data for object classification and lane detection but may fail in low-light or high-glare situations. (ii) LiDAR delivers accurate 3D mapping and distance measurements but is sensitive to adverse weather and has a high cost. (iii) RADAR functions well in poor visibility and measures speed effectively but offers lower resolution. (iv) Ultrasonic sensors are used for short-range detection but have limited range and angular coverage. To address these limitations, multi-sensor fusion is emerging as a key enabler for reliable AV operation. The proposed method combines the sensor data from multiple heterogeneous sensors to generate the most accurate, consistent, and thorough understanding of the environment. Sensor fusion enhances redundancy, reduces ambiguity, and enables better handling of uncertain or incomplete data.

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This research explores the individual contributions of different sensors but also demonstrates how sensor fusion frameworks such as Kalman filtering, probabilistic models, and neural networks is applied to integrate their outputs effectively. The comprehensions achieved through this simulation will serve as essentials for real-world implementation and further scope of the research in autonomous vehicular systems, particularly in developing safer and more intelligent vehicles.

Background of the study:

1. Sensor Fusion of LiDAR and Camera for Object Detection in Autonomous Vehicles – Wang et al., 2022.
   This research presents a deep learning-based approach to combine LiDAR data with the camera data for enhanced object detection. The authors propose a multi-modal neural network architecture that processes 3D point clouds and 2D images concurrently. The fusion strategy improves detection accuracy, especially for small and partially occluded objects. The paper highlights the benefits of complementary sensor characteristics for robust perception in diverse environments.
2. LiDAR and Vision-Based Object Detection Using YOLO and PointPillars – Kim et al., 2023.
   The paper explores the integration of YOLOv5 for image detection and PointPillars for LiDAR-based 3D object detection. The results demonstrate that combining the outputs of both detectors improves the precision and recall rates, particularly in cluttered urban environments. The fusion strategy also enables real-time processing suitable for autonomous driving.
3. Multi-Sensor Fusion for Autonomous Driving: A Review – Zhang et al., 2021
   This review outlines early, intermediate, and late fusion techniques to combine data from various sensors like LiDAR, radar, and cameras. It discusses calibration challenges, data synchronization, and the impact on perception performance. The study highlights the importance of sensor redundancy for fault-tolerant autonomous systems.
4. Real-Time Sensor Fusion for Obstacle Detection and Avoidance – Patel et al., 2022
   The paper proposes a probabilistic sensor fusion algorithm using radar, camera, and ultrasonic sensors. The approach reduces false detections and enhances stability under low visibility. Results in a simulated environment show real-time obstacle detection suitable for autonomous navigation.
5. Sensor Fusion for Autonomous Driving in Simulated Environments – Rao et al., 2021
   This study focuses on implementing sensor fusion in Gazebo for virtual testing of AV scenarios. It validates multi-sensor setups with actors like pedestrians and vehicles using MATLAB/ROS-based interfaces.
6. Simulation of Multi-Sensor Perception in MATLAB for Autonomous Vehicles – Kumar et al., 2023 The paper details a Simulink-based simulation integrating camera, radar, and LiDAR blocks in a bird's- eye view scope. The authors demonstrate how to configure and fuse sensor blocks for object tracking and adaptive cruise control, providing a practical guide for simulation-based AV development.

II. METHODOLOGY

In Autonomous driving, an Intelligent roadside perception involves the use of sensors and intelligent infrastructure facilities to present an open-source framework to estimate the distance between a vehicle equipped with perception sensors and different road objects on its path, using the association and fusion of information from different data sources. Although the solution to the perception problem is well known in the literature, it is difficult to find openly available and scalable frameworks to deploy fusion of multiple sensor data on commercially available hardware.

The objective of this methodology is to implement and evaluate a simulation framework in MATLAB where raw sensor data is generated, processed, and fused to facilitate decision-making. Unlike systems dependent on the Automated Driving Toolbox, this study uses foundational MATLAB scripting to create a transparent, customizable, and educative approach to sensor integration. Each sensor brings a unique set of advantages and limitations. LiDAR offers high-resolution 3D mapping, radar provides robustness in poor visibility, cameras deliver color and texture information, and ultrasonic sensors are more accurate and efficient for close-range detection.

By leveraging these complementary strengths, the methodology enables a holistic view of the driving environment. Ultrasonic sensors excel in close-range obstacle detection but are ineffective at longer distances. By fusing data from these diverse sources, an autonomous system can build a more complete and accurate representation of its environment, enhancing safety and decision-making capabilities.

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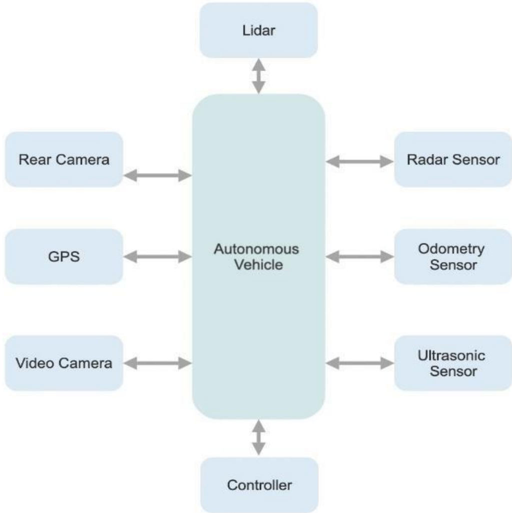

Fig 1: Sensor Integration for AV Perception and Control.

The implementation begins with the simulation of individual sensors using basic MATLAB code. Each sensor type is modelled to reflect its physical behaviour and limitations. For example, LiDAR is simulated by generating point clouds to map 3D space; radar uses polar coordinates for spatial representation with reflections from dynamic and static objects; ultrasonic sensors are simulated for short-range proximity detection; and camera vision is emulated with RGB image data and basic image processing techniques.

After individual simulation and calibration, the next step involves preprocessing the sensor data, aligning it in a common coordinate system, and then performing sensor fusion. This fusion is essential for consolidating information into a unified environmental model. Subsequently, decision-making algorithms are implemented, enabling the system to detect obstacles, classify objects, plan paths, and react to changes in real time scenarios. The system is evaluated using a range of test cases, such as obstacle avoidance, lane changes, and parking manoeuvres, with quantitative metrics to assess accuracy, responsiveness, and robustness.

Sensor Technology in Autonomous Vehicles: Sensors are the electronic devices that detects the physical quantities from the environment and map to quantitative measurement. Sensors are generally classified into the following categories: (i) camera sensor (ii) LiDAR sensor & (iii) RADAR sensor. Camera uses the environment light to detect the object. Whereas, LiDAR releases the pulse which revert back once it hits the obstacle, The RADAR is used for detection of rangeand the visuals of RADAR are as shown in the Fig 2.

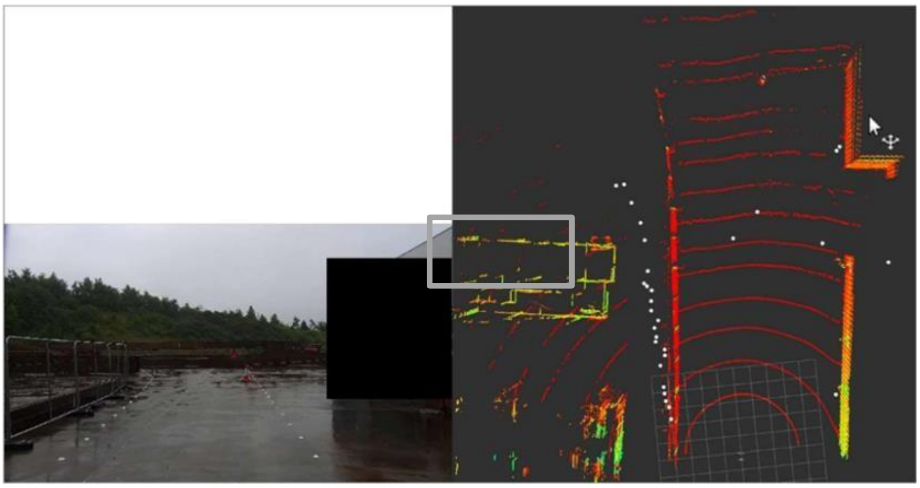

Fig 2: Visualization of RADAR

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The point cloud mentioning the coloured points are called clouds visualization of LiDAR. White points mentioned in the Fig 2 denote point cloud data of the radar. At certain distance from the radar sensor approximately between 5-7 meters, we could identify the false-positive radar which are emphasized by the grey rectangle. The RADAR sensor is operated at short distance within 19 meters.

(i) Ultrasonic Sensors: Ultrasonic sensors operate using the principle of sound wave propagation—specifically, high-frequency acoustic waves inaudible to humans, typically in the range of 40 kHz. These sensors transmit ultrasonic pulses and measure the time-of-flight (ToF) of the echo signal reflected from nearby objects to determine their distance. This method of measured using the straightforward formula:

$$\text{Distance} = (\text{Speed of Sound} \times \text{Time of Flight}) / 2$$

Ultrasonic waves are less affected by lighting conditions—unlike optical sensors such as cameras—which makes them reliable in both daytime and nighttime settings. Additionally, their effectiveness is limited to short ranges (typically up to 4–5 meters) and they have a wide beam angle, which can sometimes lead to false positives due to echoes bouncing off nearby surfaces.

Sensor Calibration and Sensor Fusion for Object Detection: Calibrations are sub-divided into intrinsic, temporal and extrinsic calibration. In case of Intrinsic calibration, internal parameters of the sensors are considered, and is carried out first and before the execution of object detection algorithms. Whereas extrinsic calibration determines the coordinates mentioning the position and also the orientation specified by the 3D axes space. The uses of sensor fusion increase the precision and confidence of detecting objects/obstacles in the driving environment. In addition, it reduces the complexity and the overall number of components, resulting in lower overall system costs. Sensor fusion algorithms used in the entire block of AV which helps in detection of sub-processes. Multi sensor data fusion with its structure is as shown in Fig 3.

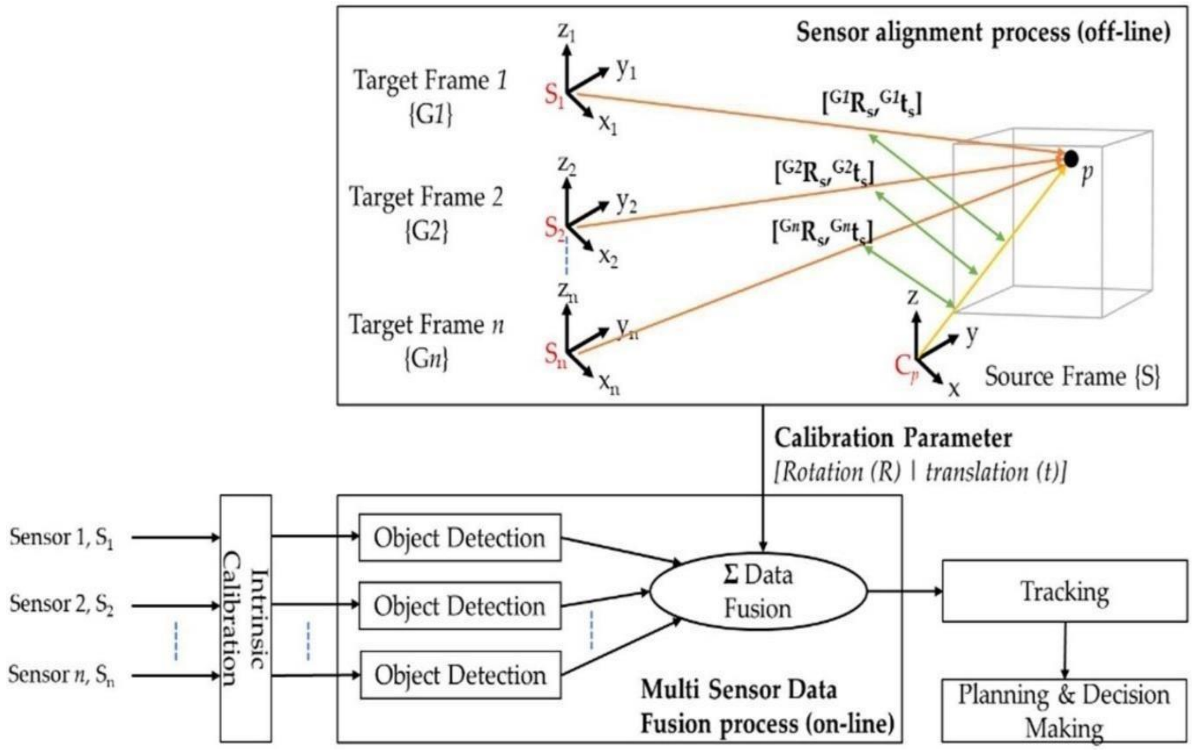

Fig 3: The Multi-Sensor Data Fusion (MSDF) structure.

The framework for 'n' sensors are arranged as per the parameters necessary for estimation process. Further, each of the sensors will provide the data or an object detected by them individually. These data helps in tracking, planning, and decision making.

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Multi-Sensor Fusion Framework for Enhancing Perception: To enhance the perception and decision capabilities in the AV, the framework of data fusion and feature extraction is implemented.

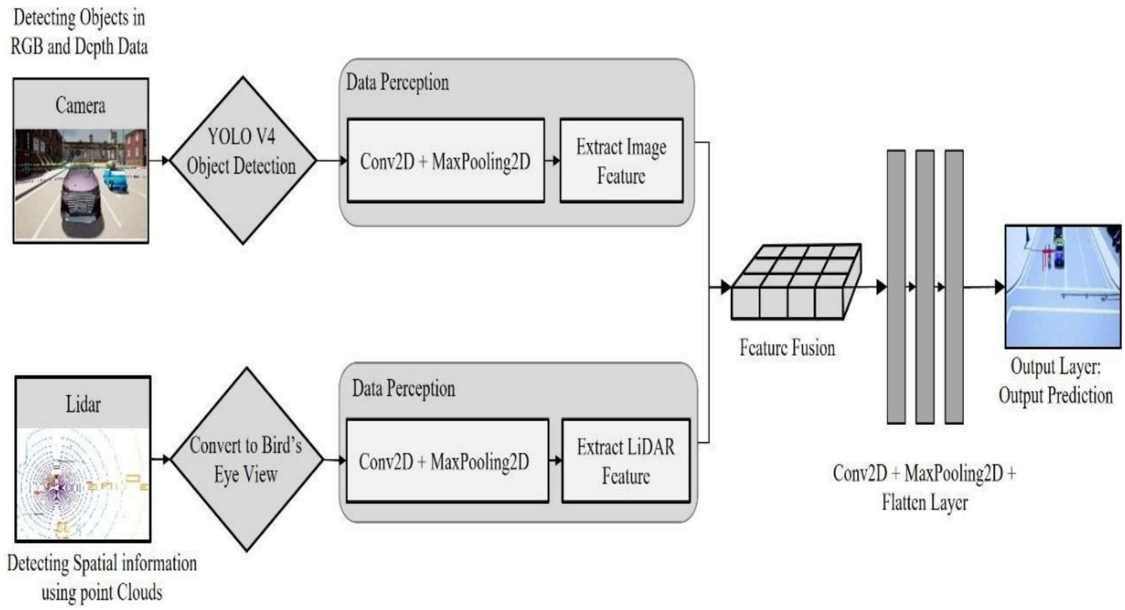

Fig 4: Feature extraction from Multi-sensor data fusion for better perception in AV

Fig 4 illustrates that, the initially detect the object using the RGB camera with depth data analysis. The detected objects can be one or more, hence the Yolo V4 algorithm is more suitable for the detection of multiple objects. Further, detection of spatial information using point clouds achieved are fed to convert the points into Bird's Eye View. The object detection and the spatial points are used for data perception generated using 2D conversion and feature extraction in both the cases. These features are combined to extract the fusion data which shall be further converted into 2D Max pooling with multi layers. The data received will involve the unwanted data within, thus the Maxpooling and CNN will help us in removing the unwanted data. Formation of multiple layers is because of the fusion of two features are considered. At the final stage, the output layer is extracted which clearly detects the objects using and provides the accurate perception decision to the user.

The refined and fused feature set is then passed into the output layer for result prediction, enabling the system to generate actionable insights such as object classifications, obstacle locations, and trajectory estimations. This multi-modal fusion approach significantly enhances the reliability, safety, and scalability of autonomous driving systems.

III. RESULTS AND DISCUSSIONS

The simulation demonstrates a simple but effective system for collision avoidance for an ego vehicle through dynamic braking strategies. The scenario involves an ego vehicle traveling at 15 m/s and a slower target vehicle ahead at 10 m/s. The goal is to detect the target vehicle, maintain a safe following distance, and brake if necessary.

The ego vehicle speed is adjusted based on the distance from the target using three zones:

- Cruising Mode (Green): When distance > 15 m.
- Caution Mode (Yellow): When 8 m < distance ⩽ 15 m.
- Emergency Braking (Red): When distance ⩽ 8 m.

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These behaviours were visualized in the simulation through coloured safety zones and a real-time status display.

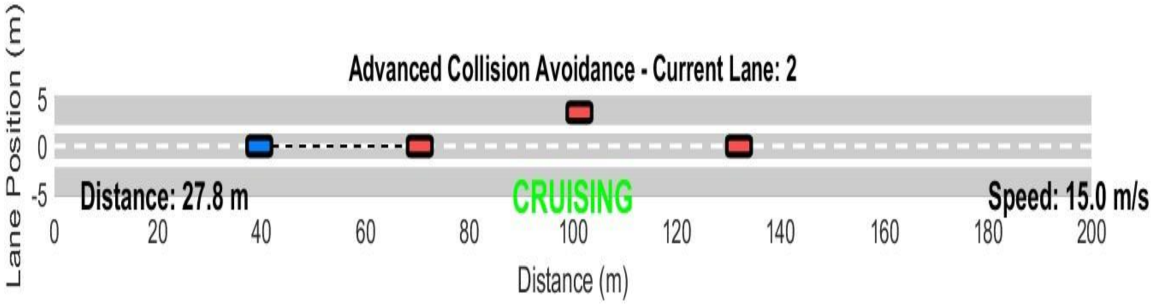

Fig 6: Cruising Graph

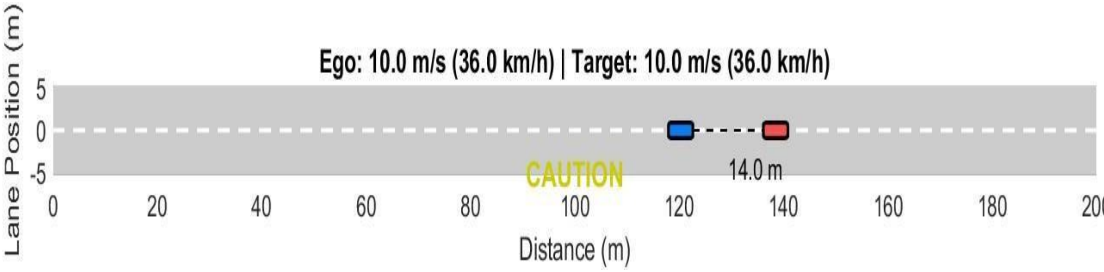

Fig 7: Caution Graph

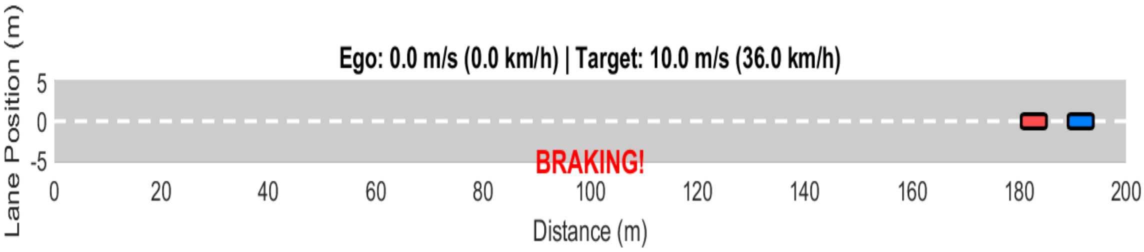

Fig 8: Braking Graph

Table 1. Experimental results of vehicle depth mapping conducted in on-road scenarios.

Scene	Vehicles	Estimated Distance (m)
Scene 1	c1	18.78
Scene 2	c1 c2	19.46 40.92
	c1	7.98
Scene 3	c2	52.42
	c3	63.15
	c4	66.56
	c1	44.6
Scene 4	c2	58.62
	c3	63.67

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Table 2: Qualification of object distance estimation using the camera sensor.

Camera	30 m	50 m	80 m	100 m
Detected/Actual object	3/3	3/3	2/3	1/3
Distance accuracy (%)	95.58	90.25	80.04	75.88

Table 3: Qualification of object distance estimation using the camera sensor.

LiDAR	30 m	50 m	80 m	100 m
Detected/Actual object	3/3	3/3	1/3	0/3
Distance accuracy (%)	98.68	97.12	96.33	95.68

Table 4: Qualification of object distance estimation using the fusion of LiDAR and camera.

LiDAR & Camera	30 m	50 m	80 m	100 m
Detected/Actual object	3/3	3/3	2/3	1/3
Distance accuracy (%)	98.02	96.32	95.89	95.02

Table 5. Distance accuracy comparison between the sensors individually & Fusion.

	Detection Range (m)	Distance Accuracy (%)
LiDAR	50	97.25
Camera	80	88.62
LiDAR + Camera	80	97.40

Tables 2–4 present the performance analysis of object detection based on LiDAR, camera, and proposed fusion sensor method and Table 4 presents a comparison of distance accuracy between the methods. The LiDAR sensor achieves the distance accuracy of 97.25% within a detection range of up to 50 meters. Whereas Camera achieves accuracy of 88.62 with the detection range of 80m. The fusion of both sensors overcomes these individual shortcomings, achieving a balanced performance with a distance accuracy of 97.25% across the full 80-meter range.

IV. CONCLUSION

This research successfully proves the importance and effectiveness of multi-sensor integration in enhancing the perception and decision-making capabilities of autonomous vehicles. By combining data from LiDAR, cameras, radar, GPS, and other sensors, a more comprehensive and accurate understanding of the vehicle's environment is achieved. The MATLAB-based simulation provides a reliable platform for developing and validating sensor fusion algorithms, enabling safer and more efficient autonomous navigation. The results emphasize that multi-sensor fusion not only improves object detection and tracking but also enhances the vehicle's ability to make intelligent driving decisions in complex and dynamic environments. This lays a strong foundation for future enhancements in autonomous vehicle technologies and real-world deployment.

REFERENCES

[1]. Maxime, D. Aurelien, P. Martial, S. Guy Le, B. "Moving Object Detection in Real-Time Using Stereo from Mobile Platform". Unmanned Syst. 2015, pp, 253–266.

DOI: 10.17148/IARJSET.2026.13120

[2]. Li, J. He, X. Li, J. “2D Lidar and Camera Fusion In 3D Modelling of Indoor Environment”. In Proceedings of the 2015 National Aerospace and Electronics Conference (NAECON), Dayton, OH, USA, 15–19 June 2015, pp. 379–383.

[3]. Varuna, D. Jamie, R. Ahmet, K. “Fusion of Lidar and Camera Sensor Data for Environment Sensing in Driverless Vehicles". arXiv 2017, arXiv:1710.06230.

[4]. G. Ajay Kumar, J.-H. Lee, and S. Kwon, "Lidar and Camera Fusion Approach for Object Distance Estimation in Self-Driving Vehicles," Symmetry, vol. 12, no. 2, pp. 324, Feb. 2020.

[5]. Wang, Z.; Wu, Y.; Niu, Q. Multi-Sensor Fusion in Automated Driving: A Survey. IEEE Access 2019, 8, pp. 2847-2868.

[6]. Geiger, A. Moosmann, F. Car, O. Schuster, B. “Automatic Camera and Range Sensor Calibration Using a Single Shot”. In Proceedings of the 2012 IEEE International Conference on Robotics and Automation (ICRA), St. Paul, MN, USA, 14–18 May 2012, pp. 3936–3943.

[7]. Rosique, F. Navarro, P.J. Fernandez, C. Padilla, A. “A Systematic Review of Perception System and Simulators for Autonomous Vehicles Research”. Sensors 2019, 19, pp. 648.

[8]. Zhang, Z. A flexible new technique for camera calibration. IEEE Trans. Pattern Anal. Mach. Intel. 2000,22(11), pp. 1330-1334.

[9]. Prakash, A. Chitta, K. Geiger, A. “Multi-Modal Fusion Transformer for End-To-End Autonomous Driving.” In Proceedings of the 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Nashville, TN, USA, 20–25 June 2021, pp. 7073–7083.

[10]. Royo, S.; Ballesta-Garcia, M. An Overview of Lidar Imaging Systems for Autonomous Vehicles. Appl. Sci.2019, 9(19), pp. 4093-4129.