

Lidar Based Intelligent Obstacle Avoidance System for Autonomous Ground Vehicles



P. Shunmuga Perumal, M. Sujasree, K. Siddhardha, K. Gokul

Abstract: Autonomous ground vehicles (AGVs) started occupying our day-to-day life. AGVs can be programmed to be smart with the current technological advancements. In doing so, we can apply them to assist humans in many aspects like reducing road accidents, enabling us to use cars without driving knowledge, autonomous patrolling in dangerous zones, and autonomous farming. For AGVs to operate at this level of automation, it must be equipped with sensory perception devices to be aware of its surroundings, and also, a way to perceive this data is crucial. As a first step towards this, researchers have developed a vast number of camera vision-based efficient neural network algorithms for detecting and avoiding obstacles. Unfortunately, an AGV cannot survive only with computer vision as it suffers from several effects like night driving and erroneous estimation of distance information. Camera vision and lidar vision together is suitable for AGVs to operate in all conditions like day, night, and fog. We propose a novel neural network model, which transforms the lidar sensor data into obstacle avoidance decisions, which is integrated into the hybrid vision of any AGV. Existing lidar sensor-based obstacle detection and avoidance systems like 2D collision cone approaches are not suitable for real-time applications, as they lag in providing accurate and quick responses, which leads to collisions. The proposed intelligent Field of View (FOV) mechanism replaces classical mathematical approaches, which accurately mimics the behavior of human drivers. The model quickly takes decisions with a high level of accuracy to command the AGV upon being obstructed with obstacles in the trajectory. This makes the AGV drive in obstacle rich environments without manual maneuvering autonomously.

Keywords: lidar sensor-based feed forward neural network, autonomous ground vehicles, obstacle detection and avoidance;

I. INTRODUCTION

An autonomous car is a vehicle, which is capable of sensing its environment using different sensors like cameras, lidars, and radars to operate without human intervention. A human driver is not required to take control of the vehicle at any point in time to drive it.

This feature enables everyone to use cars without the help of human drivers. An autonomous car can go anywhere a traditional car can. The autonomous vehicles are employed in various fields such as underwater, aerial, and ground environments, collectively termed as unmanned and autonomous vehicles. These vehicles have many applications such as rescue operations, space exploration, and food and medicine supply for soldiers in war fields. Autonomous vehicles have different complex modules such as a navigation system, the location system, mapping, global path planning, lidar perception, radar perception, computer vision-based perception, vehicle control system, and perception of vehicle speed and direction. These complex modules are smart enough to replace human drivers. [2] proposed a software architecture for autonomous vehicles, which explains various modules of the autonomous vehicles, including the environment perception, decision and planning for obstacle avoidance, and guidance and control.

Among the different modules of autonomous vehicles, the environment perception module is very crucial as this module enables the vehicles to detect and avoid obstacles in the operating environments. An increase in applications of autonomous ground vehicles led to research in obstacle detection and avoidance systems. The obstacle detection part can be built using sensors like lidars, radars, ultrasonic sensors, and cameras. The obstacle avoidance part processes the data acquired by these sensors in order to provide control decisions to the vehicle.

The following sections discuss the literature review, the layered and functional architectures of the proposed lidar assisted intelligent obstacle avoidance system, experimental setups, and results.

II. RELATED WORKS

This section discusses various approaches developed for obstacle detection and avoidance using classical mathematical approaches and neural networks. There are various approaches for obstacle avoidance methodology. One such approach is the 2D or 3D collision cone construction of the obstacle [5]. This collision cone, along with the heading direction of the vehicle, is exploited to identify the control decision needed for the autonomous ground vehicle to move further.

An autonomous robot has hardware and software architecture frameworks for its operation. The architecture includes sub-systems like obstacle detection and avoidance, guidance and control, navigation. This article contributes to the development of obstacle detection and avoidance, where existing guidance and control, navigation algorithms are used.

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Autonomous robots and vehicles must be able to detect nearby obstacles or vehicles in operating environments. [1] presents a systematic, comprehensive survey for vehicle detection and collision avoidance. This survey also details about the selection of low cost and long-range sensors.

Obstacle avoidance attracted the attention of researchers before few decades. In [3], a method named vector field histogram was proposed to simultaneously avoid collision with obstacles and steer the mobile robot towards the target. In [4], a dynamic window approach for collision avoidance was proposed, which helps the mobile robots to move through obstacle-free trajectories.

A collision cone approach for collision detection and avoidance between irregularly shaped obstacles was proposed in [5], where the collision geometry is calculated for every obstacle, which is computationally complex. A multilayer architecture for real-time obstacle detection-based path planning for autonomous helicopters is developed in [6].

Obstacle avoidance for aerial vehicles involves different approaches, some of which can also be implemented in ground vehicles. A novel technique to produce continuously differentiable flight trajectories with the presence of arbitrarily shaped no-fly zones and obstacles are fixed at that point in time was proposed in [7]. The problem of finding an optimal trajectory between two nodes of the core-path graph is solved via a minimum cost path search algorithm. Obstacle detection and avoidance features are also mandatory for Unmanned Aerial Vehicles (UAVs). In [8], a fluid mechanics-based obstacle avoidance method was proposed for UAVs.

A dynamical system based real-time obstacle avoidance method was proposed in [9], which involves complex computations that mandates robot to depends on the shape of obstacles. An autonomous vehicle can be subjected to both static and moving obstacles. Avoiding static obstacles is simpler than moving obstacles. Moving obstacle avoidance methodology should consider the velocities and heading direction of the obstacles. [10] proposes and validates a framework for avoiding moving obstacles during navigation through visual data with a wheeled robot. When validated in real outdoor experiments, considering obstacle velocities provides more smooth, safe, and quick robot behavior than when it is not taken into account.

The autonomous vehicle market urged the industries to develop good quality of efficient range sensors such as the Velodyne lidar sensor to generate point cloud information about the road environment, including obstacles. [11] proposed a method for lidar point cloud processing to generate obstacle map generation, which is used along with the lane map generated. Obstacle avoidance capability is also required for unmanned aerial vehicles. [12] – [15] developed path planning algorithms using classical complex mathematical modelling to route the unmanned aerial vehicles in obstacle environments. [16] proposed an innovative and simple solution for obstacle detection and collision avoidance of unmanned aerial vehicles (UAVs).

The low-level vehicle control system executes obstacle avoidance strategies planned by the sensors and computing devices. [17] proposed a real-time, rapidly exploring random tree algorithm, which shares obstacle information among vehicles for path planning. [18] proposed a novel design of a driving control system, which includes both longitudinal and lateral controllers for autonomous vehicles. [19] presented a strategy for real-time collision avoidance by rejecting the external disturbances and generating real-time motion in the presence of obstacles. [20] proposed a neural network-based guidance methodology for docking autonomous Vehicles. In this approach, systematic motion errors of the vehicle are reduced iteratively by executing the corrective motion commands, generated by the NN, until the vehicle achieves its desired pose within random noise limits.

[21] proposed an approach for classifying the tracks of all visible objects. This track classification method uses a mathematical method of combining log-odds estimators, which is fast enough for real-time use. [22] have proposed an approach for mobile robot navigation using a neural controller in unstructured environments, which simultaneously learns obstacle avoidance and target seeking without any explicit behavior switching schemes. This approach is capable of working with unmapped environments with many obstacles of different shapes and sizes. However, still, this approach needs a considerable volume of training data, which increases complexity. [23] proposed an approach for vehicle detections by clustering the appearance patterns. The proposed model ultimately survives on computer vision to identify the vehicle orientations, which may not be sufficient during night times. Hence a lidar-based vision system is required.

[24] developed an approach to detect 3D objects for autonomous vehicles by encoding the point clouds into descriptive volumetric representation, which is further connected to a neural network to generate detections. [25] proposed a deep reinforcement learning-based algorithm for obstacle avoidance using a monocular RGB vision. [26] proposed a deep learning-based approach with a tensor flow framework to navigate a driverless car through an urban environment. This approach uses AlexNet's deep learning model for identifying driving intelligence. [27] developed a recurrent neural network model based steering control system for autonomous vehicles for dealing with the steering actuator dynamics. This model effectively generates commands for the low-level vehicle control systems.

[28] proposed a lidar-video dataset based approach, which provides large-scale, high-quality point clouds scanned by lidar sensors and videos recorded by dashboard cameras. This approach exposes the need for hybrid vision systems for autonomous vehicles. [29] developed a library using artificial intelligence-based methods for obstacle detection, which has three methods, namely the multilayer perceptron neural network, self-organizing map, and support vector machine. Further, this library is integrated into a co-simulation framework for obstacle recognition using sensory data.

[30] presented an approach for the detection of real-time obstacles and their status classification, which can be used by the collision warnings of autonomous vehicles. [31] developed a concept of end-to-end imitation learning for autonomous robots using a composite architecture of the convolutional neural network and long-short term memory neural network. [32] developed a model for object detection from lidar sensor data in self-driving cars.

[33] proposed an approach to detect real-time vehicles by fusing vision and lidar point cloud information. In this approach, the obstacles are detected by the grid projection method with lidar point cloud information, and then the obstacles are mapped to the image to get regions of interest.

From the literature survey, it is very clearly observed that that computer vision alone not sufficient to provide an efficient vision for autonomous vehicles. This motivated us to propose a lidar-based intelligent obstacle detection and avoidance system, which can be integrated into autonomous vehicles to provide hybrid vision.

III. PROPOSED LIDAR ASSISTED INTELLIGENT OBSTACLE AVOIDANCE SYSTEM

In this section, we present the layered and functional architecture of the proposed system.

A. Layered Architecture

The proposed system is implemented as a three-layered architecture, which includes obstacle detection layer, obstacle avoidance layer, and vehicle control layer, as shown in Figure 1.

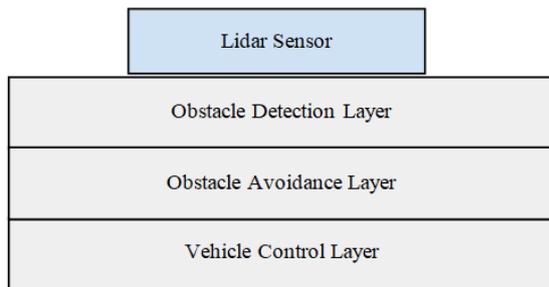


Figure 1: The three-layered architecture of the proposed obstacle avoidance system

Obstacle Detection Layer: This layer Sensing layer is responsible for handling the lidar sensor. This layer rotates the lidar platform horizontally in the 2D plane to detect the presence of obstacles. This pan motion is identified with the azimuthal angle (α). This layer operates as thread, that is, implemented as an independent layer from other layers. So this layer continuously operates the lidar and collects distance and angle of the laser beam. (Lidar sensor and servo motor). This layer is responsible for detecting obstacles in the safe Field of View (FOV). This layer is also implemented as thread, that is, the independent layer.

Obstacle Avoidance: This layer is responsible for guiding the AGVs to avoid obstacles in the operating environment. The existence of the obstacles detected by the obstacle detection later is given to the obstacle avoidance layer, which calls the proposed feed-forward neural network to make the decision to avoid the obstacles in the trajectory.

Vehicle Control Layer: This layer is responsible for executing the low-level vehicle control commands to drive the AGV in the trajectory planned for the AGV's mission. This layer interfaces the low-level vehicle entities like wheels, motor drivers to the controller, which is controlled by the main computer.

B. Architecture of the Proposed Obstacle Detection and Avoidance System

In this section, we discuss the overall functional architecture of the obstacle detection and avoidance system for autonomous ground vehicles. The proposed architecture is shown in Figure 2, which will be deployed in autonomous ground vehicles. It consists of an obstacle detection module, obstacle avoidance module, and vehicle control system module, and are explained in the following subsections. Besides, the flow chart of the proposed obstacle detection and avoidance system is also explained.

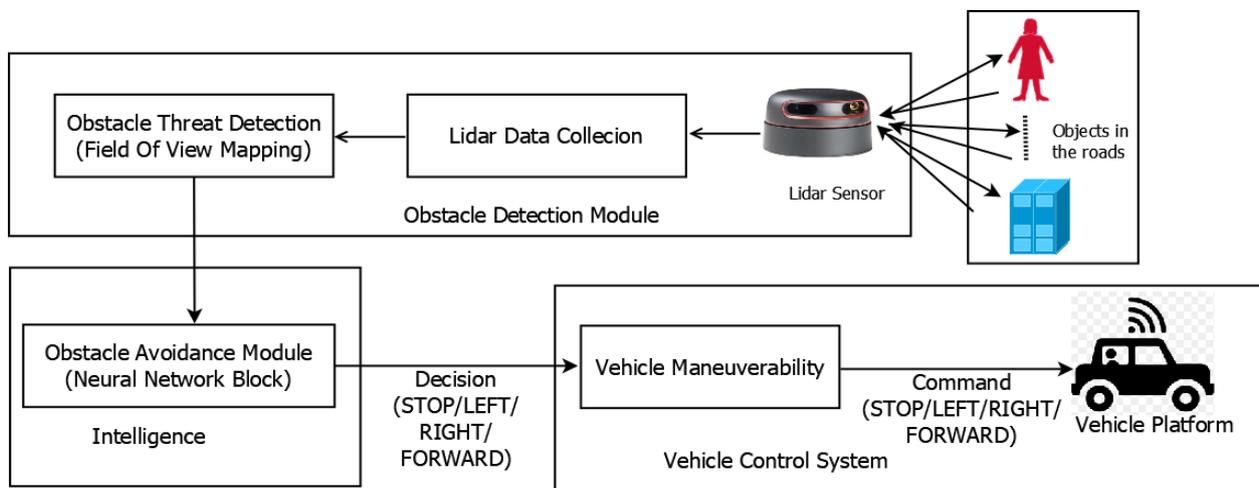


Figure 2: Functional Architecture of the proposed obstacle detection and avoidance system

Obstacle Detection Module: Autonomous vehicles are operated in a complex environment filled with varieties of obstacles like pedestrians, buildings, and other vehicles. These obstacles are to be detected by the autonomous vehicles so that they can avoid them without collision.

This subsection explains the working of the obstacle detection module, which detects obstacles in front of autonomous ground vehicles. This module has a lidar sensor module, lidar data collection, mapping of the lidar data into the FOV, and obstacle threat detection module, which are explained as follows.

Lidar sensor assisted obstacle detection: Generally, autonomous vehicles get a hybrid vision from multiple modalities like cameras, lidar, and radar. Lidar sensors work with reliability in various conditions, where camera visions fail. Hence, the proposed lidar-based obstacle detection system can be deployed in autonomous ground vehicles to provide hybrid-vision. The obstacle detection module uses a lidar sensor to detect obstacles in the operating environment. This module fires and receives the laser pulses in a controlled manner on the Field of View (FOV) of the autonomous vehicle, where the orientation of the laser beams is known to the system.

The proposed obstacle detection system uses the Lidar Lite V3 sensor, which is a single point laser with 900m wavelength and 40m range. The lidar sensor is mounted on top of the AGV, such that it always moves in XY (2D plane). The motion of the lidar sensor is controlled by the

high precision servo motor, which ensures that the laser beams are sliding/sweeping in X, Y plane within a predefined range to form the Field of View (FOV) for the AGV.

Lidar data collection: The lidar data collection module continuously collects the distance-angle pair of the lidar beams, as the lidar sensor fires the laser beams. These collected data will be enqueued in the lidar data queue for further processing. The range for lidar sensor beam sweep in the 2D plane is defined from -60 degrees to +60 degrees, which is 120 degrees wide.

The obstacle threat detection modules read the lidar queue data continuously and map into the FOV triangle, which is explained in the next section.

Obstacle threat detection module using mapping of the lidar data into FOV: The proposed system defines FOV in three orientations, namely 'straight FOV,' 'left FOV,' 'right FOV,' with respect to the heading direction of the AGV in order to guide the AGV to avoid obstacles. The FOV of the AGV is split into 120 portions, where each portion is of 1 degree, as shown in Figure 4. Hence the total number of lines formed by the lidar laser beams on both the left and right portion of the FOV is 121, where each line has its distance (dm) and angle (m) value with respect to the lidar sensor mounting position and heading direction of the AGV. Figure 4 shows the straight FOV.

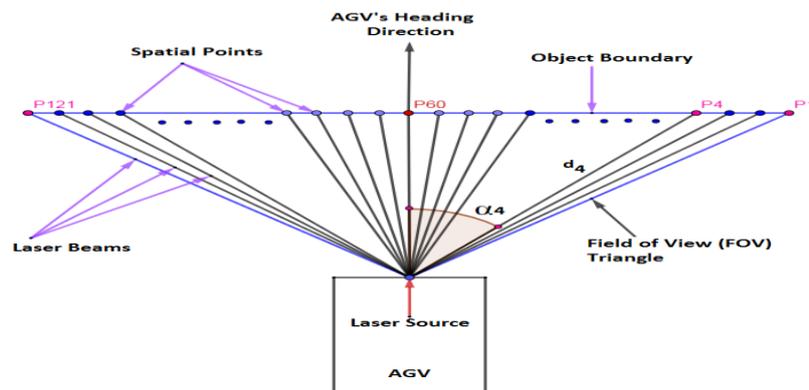


Figure 4: Top view of the FOV Triangle formed between the laser source and the object boundary with respect to the heading direction of the AGV.

In 'straight FOV,' the lidar beam AP61 passes through the axis of AGV's heading direction, say AH. For left FOV, the lidar beam AP61 forms 90° with AH in the anti-clockwise direction, and for right FOV, the lidar beam forms 90° with AH in the clockwise direction. When AGV detects any obstacle in the straight FOV, it will intend to avoid the obstacle by turning into either the left or right side. When it decides to turn the left side, the AGV should check whether there is any obstacle in the left-FOV. If there is no obstacle in the left-FOV, the AGV will turn left and move. Otherwise, it will check the right-FOV. Hence the FOV is switched between straight/left/right based on the obstacle that exists in the trajectory of the AGV.

The threshold distance, that is, the safe distance between the AGV and obstacle, is assumed to be 100cm. When the length of AP61 is 100cm or above and when the

line connects P1-P121 is perpendicular to the heading direction of the AGV, the AGV has no obstacle threat. Now, the P1-P121 line lies in a safe place. However, when the length of AP61 is less than 100cm, and when P1-P121 is perpendicular to the heading direction of the AGV, the AGV has an obstacle threat in the straight FOV. Now, the P1-P121 line lies in an unsafe place.

The proposed system is capable of mapping the lidar beam distance-angle data into the three FOVs to detect the existence of obstacles in the trajectories of AGV. If any obstacle threat is present in the FOV, then the vehicle should be stopped and should change its moving course to avoid collision with the obstacle, as explained in the next subsection.

Obstacle Avoidance Module: This module is responsible for making decisions towards avoiding obstacles. The services provided by this module is accessed only when the obstacle detection layer notifies the presence of obstacles in critical distances. Hence whenever the AGV detects any obstacle threat in its trajectory, it simply calls the obstacle avoidance module.

A novel neural network is proposed, which is capable of transforming the lidar sensor data collected in the FOVs

into decisions to avoid obstacles. This module is the core brain of the proposed system, which is implemented using the novel “end to end multi-layered feedforward neural network.” The structure of the proposed neural network is fixed with 242 input neurons, 80 hidden neurons, and four output neurons, as shown in Figure 5.

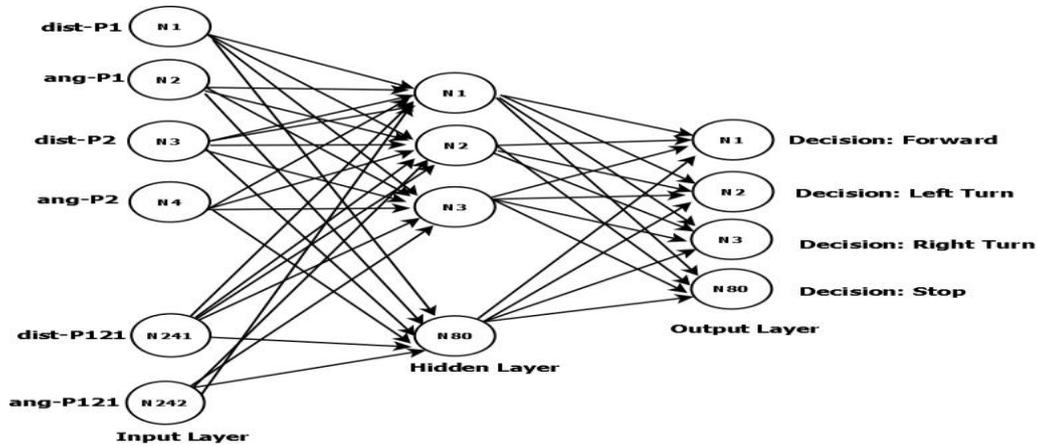


Figure 5: Proposed Lidar Sensor Data based Feed Forward Neural Network

The 242 input neurons are required to feed the neural network with the distance-angle pair data given by the lidar sensor in the FOV. The four output neurons are used to provide four classes of decisions like forward, stop, left-

turn, and right-turn, which are further used by the vehicle control system to maneuver the AGV in the desired trajectory. Table 1 shows the structure of the proposed neural network.

Table 1: The Structure of the Proposed Lidar Neural Network

Number of input neurons	242 (Each lidar sensor sweep data contains 121 pairs of distance-angle data; Hence the total is 242)
Number of hidden neurons	80
Number and labels of the output classes (decisions taken by the network)	4 (Forward, Left, Right, Stop)
Number of training dataset for the output class ‘Forward’	50,000 pairs of distance-angle pair data
Number of training dataset for the output class ‘Left’	50,000 pairs of distance-angle pair data
Number of training dataset for the output class ‘Right’	50,000 pairs of distance-angle pair data
Number of training dataset for the output class ‘Stop’	50,000 pairs of distance-angle pair data

This training data set is used to learn the weights and biases parameter of the neural network. This input data, along with the neural network’s learned parameters (weights and biases), are used to guide the vehicle. The network is trained using stochastic gradient descent and the backpropagation algorithm.

Vehicle Control System Module: This section explains about the vehicle control system module, which is responsible for maneuvering the autonomous vehicle. This module receives commands from the main computer over interrupt communication. Based on the existence of

obstacles in the trajectory of the AGV, the main computer generates commands to maneuver the AGV by stopping or turning left or turning right.

C. Flow chart of the proposed obstacle detection and avoidance system

The following Figure 6 is a flow chart, which clearly shows the transformation of lidar data into knowledge to take obstacle avoidance decisions.



This flow chart implements the proposed obstacle detection and avoidance system with threads.

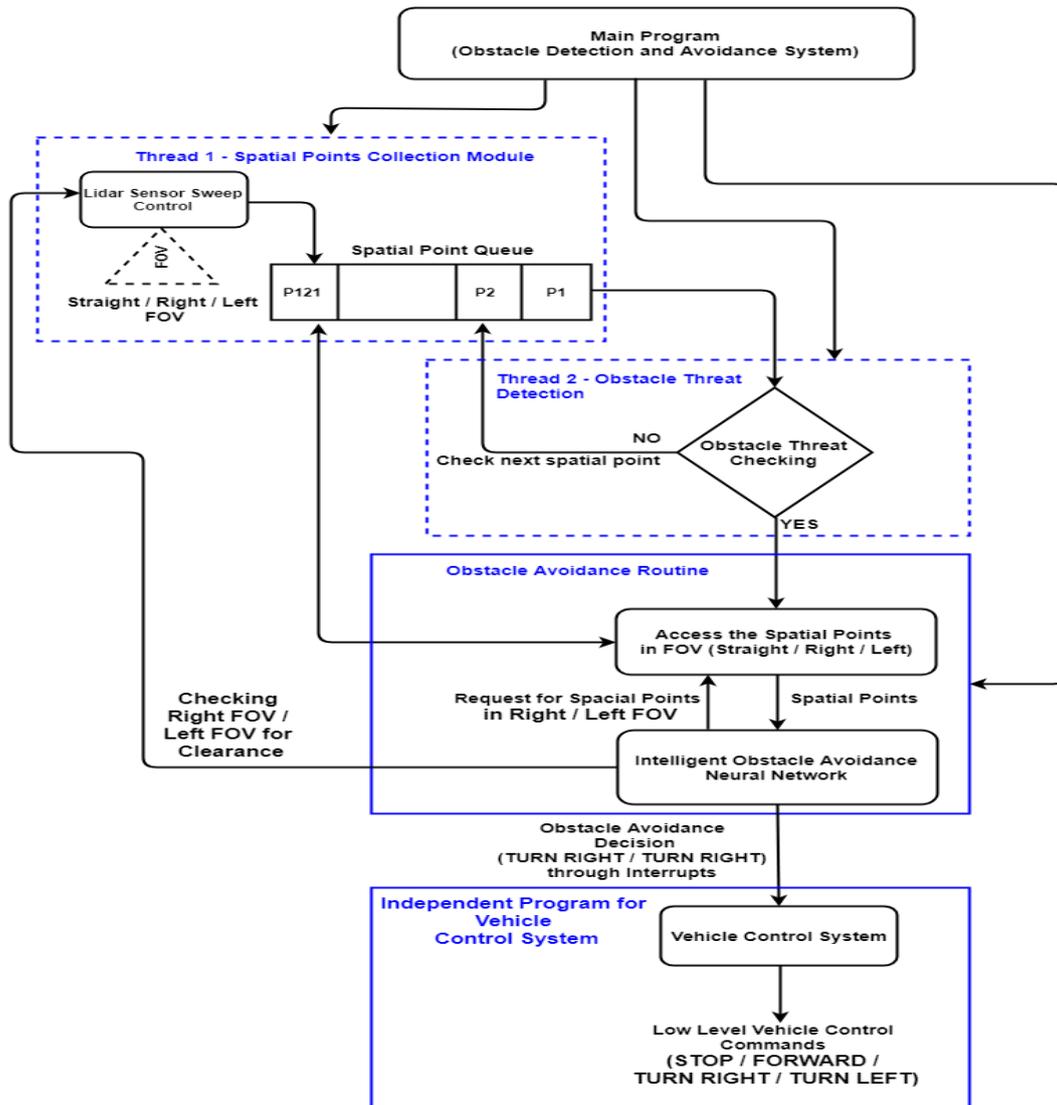


Figure 6: Flow Diagram of the Proposed Obstacle Detection and Avoidance System

IV. EXPERIMENTS AND RESULT ANALYSIS

This section explains the experimental setup, performance analysis of the system.

A. Experimental Setup

The proposed obstacle detection and avoidance system is implemented and experimented in real-time scenarios. The system is built using a lidar lite V3 sensor, raspberry pi 3 board, Arduino mega 2560 board, mobile robot platform based on 12v DC motors, and motor driver. The lidar lite v3 is a single point lidar sensor, which is rotated using high precision servo motor (make) to fire the lidar in the desired FOV. The raspberry pi computer controls the operation of the lidar sensor, data collection, mapping the lidar data into FOV, executing the proposed feed-forward neural network to convert the FOV data into decisions. The complete vehicle control system, that is, vehicle maneuverability, is implemented in the Arduino board. Once the raspberry pi 3 computer takes any decision like stopping of the AGV, turning the AGV into left or right, then it immediately interrupts the Arduino board. Based on the

commands transmitted by the main computer, the Arduino board controls the maneuverability of the AGV. The hardware assembly of the proposed system is shown in Figure 7.



Figure 7: Hardware setup of the proposed obstacle detection and avoidance system

B. Performance Analysis

This subsection analyses the performance of the proposed system by comparing it with the standard classical 2D collision cone approach.

The proposed system is tested for various numbers, locations, sizes, shapes, distance parameters with respect to the obstacles and autonomous ground vehicles, as discussed in the following subsections.

The proposed system's performance is compared with the existing classical 2D Collision Cone (2DCC) approach.

Regular shaped obstacles: The performance of the proposed Obstacle Detection & Avoidance (ODA) system for avoiding rectangular-shaped obstacles is compared with the classical 2D collision cone approach through repeated experiments.

The obstacles are located in the three FOVs (Straight-FOV, Right-FOV, Left-FOV) of the AGV's trajectory, and experiments are carried out. The safe threshold distance between the AGV and the obstacles are assumed to be 100cm. The experimental results are plotted in Figure 8. From Figure 8, it is observed that the proposed ODA approach avoids obstacles quickly than the classical 2D collision cone approach. This highly reduces the chances of collisions between the AGVs and obstacles.

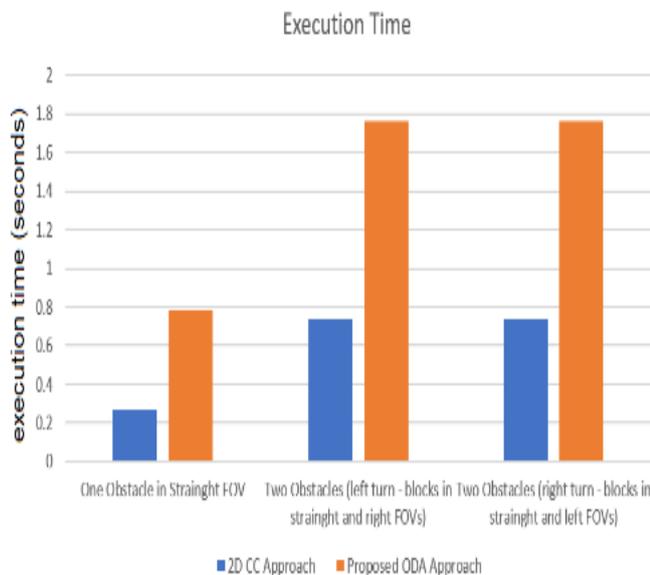


Figure 8: Comparison of time consumption of both the proposed ODA and 2D Collision approaches

Avoiding irregularly shaped obstacles: The following Figure 9 (a) and Figure 9 (b) show the trajectories planned by both the proposed system and 2D collision cone approaches when an obstacle is found in the trajectory of the AGV. The classical 2D collision cone approach considers the boundary points in region 1 (R1) as only the boundary points on the safe distance plane are considered for obstacle avoidance. Hence the 2D collision cone approach ignores the Regions 2 (R2). However, the proposed obstacle detection and avoidance system consider R1, regions 2 (R2), and regions 3 (R3), as the proposed lidar point-based neural network is trained with a huge volume of datasets including the case shown in Figure 9.

V. CONCLUSIONS & FUTURE ENHANCEMENT

A novel lidar vision-based intelligent obstacle detection and avoidance feed-forward neural network for autonomous ground vehicles is proposed, which outperforms the classical mathematical approaches like the 2D collision cone

approach. With proposed algorithm and the developed

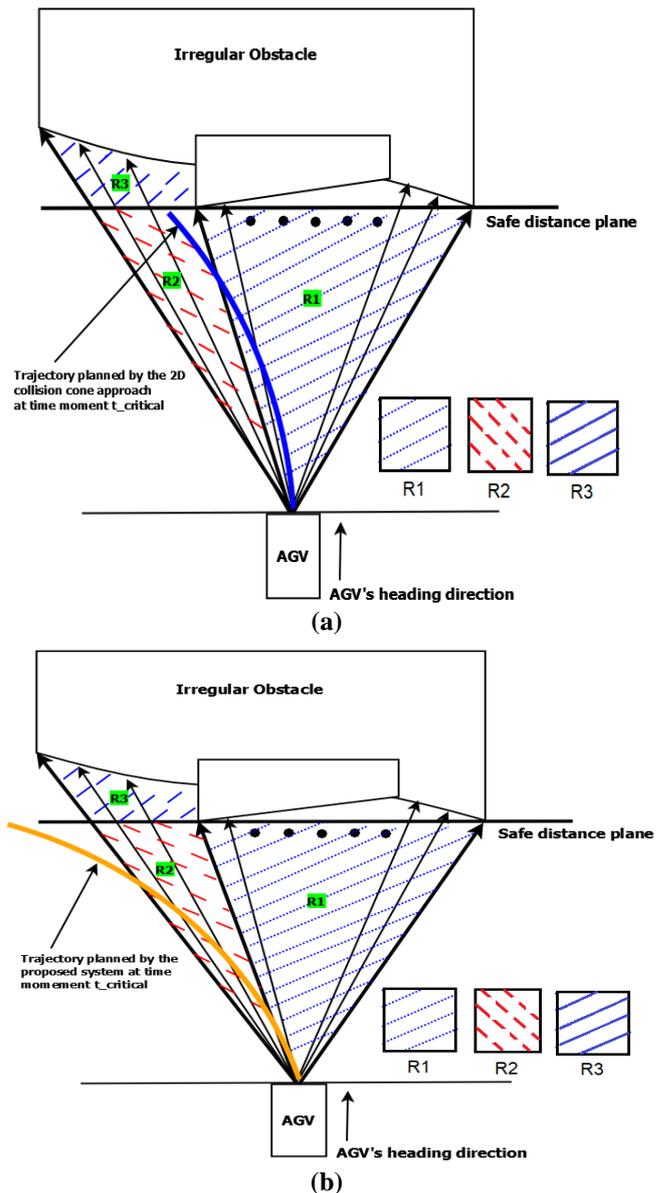


Figure 9: Avoiding irregular obstacle

From Figure 9(a) & (b), it is obvious that the proposed obstacle detection and avoidance system outperforms the classical mathematical based obstacle avoidance approaches. The classical 2D collision cone approach leads the AGV into the critical collision cone (R3) when it only considers the R1. Once when the AGV enters into the R3, then the 2D collision cone approach will calculate the safety measures and maneuvers the AGV away from the collision. This consumes extra time, which is not suitable for time-critical AGV applications. In contrast to the 2D CC approach, the proposed ODA approach predicts the collision in R3 in advance and hence maneuvers the AGV accordingly. This saves decision taking time with accuracy and avoids collisions in advance.

AGV, we experimented in real-time environments with different trajectories and various shapes of obstacles. The experiment results show that our method consumes less time for taking obstacle avoidance decisions than the existing classical mathematical based obstacle avoidance approaches. Also, the experiments indicate that our algorithm is capable of deviating the AGV from collision risks well in ahead than the classical approaches.

REFERENCES:

- Mukhtar, A., Xia, L. and Tang, T.B., 2015. Vehicle detection techniques for collision avoidance systems: A review. *IEEE Transactions on Intelligent Transportation Systems*, 16(5), pp.2318-2338.
- Zong, W., Zhang, C., Wang, Z., Zhu, J. and Chen, Q., 2018. Architecture design and implementation of an autonomous vehicle. *IEEE Access*, 6, pp.21956-21970.
- Borenstein, J., 1989. The vector field histogram-fast obstacle avoidance for mobile robots. *IEEE Trans. Syst. Man Cybernet.*, 19, pp.1179-1187.
- Fox, D., Burgard, W. and Thrun, S., 1997. The dynamic window approach to collision avoidance. *IEEE Robotics & Automation Magazine*, 4(1), pp.23-33.
- Chakravarthy, A. and Ghose, D., 1998. Obstacle avoidance in a dynamic environment: A collision cone approach. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 28(5), pp.562-574.
- Redding J, N. Amin J, and D. Boskovic J., 2007. A Real-time Obstacle Detection and Reactive Path Planning System for Autonomous Small-Scale Helicopters. *AIAA Guidance, Navigation and Control Conference and Exhibit*, South Carolina, pp.1-22.
- Mattei, M. and Blasi, L., 2010. Smooth flight trajectory planning in the presence of no-fly zones and obstacles. *Journal of guidance, control, and dynamics*, 33(2), pp.454-462.
- Cruz, G.C.S. and Encarnação, P.M.M., 2012. Obstacle avoidance for unmanned aerial vehicles. *Journal of Intelligent & Robotic Systems*, 65(1-4), pp.203-217.
- Khansari-Zadeh, S.M. and Billard, A., 2012. A dynamical system approach to real time obstacle avoidance. *Autonomous Robots*, 32(4), pp.433-454.
- Cherubini, A., Spindler, F. and Chaumette, F., 2014. Autonomous visual navigation and laser-based moving obstacle avoidance. *IEEE Transactions on Intelligent Transportation Systems*, 15(5), pp.2101-2110.
- Zhu, H., Fu, M., Yang, Y., Wang, X. and Wang, M., 2014, October. A path planning algorithm based on fusing lane and obstacle map. In *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)* (pp. 1442-1448). IEEE.
- Chen, H., Chang, K. and Agate, C.S., 2013. UAV path planning with tangent-plus-Lyapunov vector field guidance and obstacle avoidance. *IEEE Transactions on Aerospace and Electronic Systems*, 49(2), pp.840-856.
- Yao, P., Wang, H. and Su, Z., 2015. Real-time path planning of unmanned aerial vehicle for target tracking and obstacle avoidance in complex dynamic environment. *Aerospace Science and Technology*, 47, pp.269-279.
- Wang, H., Lyu, W., Yao, P., Liang, X. and Liu, C., 2015. Three-dimensional path planning for unmanned aerial vehicle based on interfered fluid dynamical system. *Chinese Journal of Aeronautics*, 28(1), pp.229-239.
- Peng, Y., Honglun, W. and Zikang, S., 2015. UAV feasible path planning based on disturbed fluid.
- Gageik, N., Benz, P. and Montenegro, S., 2015. Obstacle detection and collision avoidance for a UAV with complementary low-cost sensors. *IEEE Access*, 3, pp.599-609.
- Zheng, Z., Liu, Y. and Zhang, X., 2016. The more obstacle information sharing, the more effective real-time path planning?. *Knowledge-Based Systems*, 114, pp.36-46.
- Xu, L., Wang, Y., Sun, H., Xin, J. and Zheng, N., 2015. Integrated longitudinal and lateral control for Kuafu-II autonomous vehicle. *IEEE Transactions on Intelligent Transportation Systems*, 17(7), pp.2032-2041.
- Hildebrandt, A.C., Wittmann, R., Sygulla, F., Wahrmann, D., Rixen, D. and Buschmann, T., 2018. Versatile and robust bipedal walking in unknown environments. Preprint-submitted for publication.
- Wong, J., Nejat, G., Fenton, R.G. and Benhabib, B., 2006, September. Neural-network-based docking of autonomous vehicles. In *2006 IEEE Intelligent Transportation Systems Conference* (pp. 1574-1579). IEEE.
- Teichman, A., Levinson, J. and Thrun, S., 2011, May. Towards 3D object recognition via classification of arbitrary object tracks. In *2011 IEEE International Conference on Robotics and Automation* (pp. 4034-4041). IEEE.
- Patnaik, A., Khetarpal, K. and Behera, L., 2014. Mobile robot navigation using evolving neural controller in unstructured environments. *IFAC Proceedings Volumes*, 47(1), pp.758-765.
- Ohn-Bar, E. and Trivedi, M.M., 2015. Learning to detect vehicles by clustering appearance patterns. *IEEE Transactions on Intelligent Transportation Systems*, 16(5), pp.2511-2521.
- Du, X., Ang, M.H. and Rus, D., 2017, September. Car detection for autonomous vehicle: LIDAR and vision fusion approach through deep learning framework. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 749-754). IEEE.
- Xie, L., Wang, S., Markham, A. and Trigoni, N., Towards monocular vision based obstacle avoidance through deep reinforcement learning. arXiv 2017. arXiv preprint arXiv:1706.09829.
- Gallardo, N., Gamez, N., Rad, P. and Jamshidi, M., 2017, June. Autonomous decision making for a driver-less car. In *2017 12th System of Systems Engineering Conference (SoSE)* (pp. 1-6). IEEE.
- Garimella, G., Funke, J., Wang, C. and Kobilarov, M., 2017, September. Neural network modeling for steering control of an autonomous vehicle. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 2609-2615). IEEE.
- Chen, Y., Wang, J., Li, J., Lu, C., Luo, Z., Xue, H. and Wang, C., 2018. Lidar-video driving dataset: Learning driving policies effectively. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 5870-5878).
- Castaño, F., Beruvides, G., Haber, R. and Artuñedo, A., 2017. Obstacle recognition based on machine learning for on-chip LiDAR sensors in a cyber-physical system. *Sensors*, 17(9), p.2109.
- Song, W., Yang, Y., Fu, M., Qiu, F. and Wang, M., 2017. Real-time obstacles detection and status classification for collision warning in a vehicle active safety system. *IEEE transactions on intelligent transportation systems*, 19(3), pp.758-773.
- Fu, Y., Jha, D.K., Zhang, Z., Yuan, Z. and Ray, A., 2019. Neural Network-Based Learning from Demonstration of an Autonomous Ground Robot. *Machines*, 7(2), p.24.
- Herzog, M. and Dietmayer, K., 2019. Training a Fast Object Detector for LiDAR Range Images Using Labeled Data from Sensors with Higher Resolution. arXiv preprint arXiv:1905.03066.
- Wang, H., Lou, X., Cai, Y., Li, Y. and Chen, L., 2019. Real-Time Vehicle Detection Algorithm Based on Vision and Lidar Point Cloud Fusion. *Journal of Sensors*, 2019.

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