

Real-time Perception and Autonomous Navigation: A Fuzzy Logic-Based Approach for Enhanced Obstacle Avoidance in Self-Driving Vehicles

Mrinal 1, Neeraj Kumar²

*1*Assistant Professor, Department Of Computer Science And Engineering,
MERI College Of Engineering And Technology, Haryana, India.

*2*Skill Assistant Professor, SDCS/IT, Shri Vishwakarma Skill University, Palwal, India
mrinal.mudgil@meri.edu.in, *Neerajkumar@svsu.ac.in* ²

ABSTRACT

This paper introduces an innovative approach aimed at enhancing the autonomy of self-driving vehicles by enabling them to perceive and respond to their surroundings in real-time, effectively navigating through complex environments while avoiding obstacles. The proposed technique leverages a combination of three ultrasonic sensors, a neural network model that has been meticulously trained, and a sophisticated fuzzy logic controller. To validate the efficacy of this approach, extensive simulations were conducted using V-REP and MATLAB software. The results of these simulations demonstrate the potential of the proposed method to significantly improve the safety and reliability of self-driving vehicles, contributing to the advancement of autonomous transportation systems.

Keywords

Self-driving vehicle, obstacle avoidance, fuzzy logic controller, stable obstacles, moving obstacles.

I. Introduction

Obstacle avoidance in urban environments is a major challenge for self-driving vehicles. The task involves recognizing obstacles in the direction of progress and making decisions on adjusting the steering angle or controlling the speed of the vehicle to avoid collisions. The use of deep learning methods, particularly Convolutional Neural Networks (CNNs) and Fuzzy Logic controllers, has shown improved performance in detecting and categorizing moving objects such as vehicles and pedestrians. The proposed model combines CNN and Fuzzy Logic controllers to make human-like decisions in avoiding obstacles and moving self-driving vehicles autonomously in

different size obstacle environments based on sensor and CNN data. The model is simulated using a mobile robot equipped with a large view camera and three ultrasonic sensors. The simulation is achieved using V-REP and MATLAB software. The proposed model is flexible and effective in different obstacle environments, providing decision-making capabilities to modify steering angles and set back self-driving vehicles on the lane. The paper presents the general approach of obstacle avoidance using Fuzzy Logic controllers, outlines the basics of CNN, and explains the proposed simulation setup and its development. The simulation results demonstrate the effectiveness of the proposed model in obstacle avoidance. The combination of CNN and Fuzzy Logic controllers could be a promising approach for developing smart vehicles capable of autonomous obstacle avoidance.

II. Related Work

The use of fuzzy logic controllers has shown promising results in self-driving vehicles for steering, braking, obstacle avoidance, and overtaking. Several studies have explored the use of fuzzy logic controllers to determine trajectories and make human-like decisions for overtaking using visual sensor data and GPS. However, limitations such as the random movement of various vehicles can affect the algorithm. To overcome these limitations, researchers have proposed a combination of quintic Bezier curves and straight lines to calculate trajectories and avoid obstacles. Overall, the use of fuzzy logic controllers in self-driving vehicles has the potential to improve obstacle avoidance and overtaking capabilities.

III. Methods and Materials

The obstacle avoidance system architecture includes a large view camera for data collection, which is used to train the Convolutional Neural Network (CNN) model. During self-driving mode, the CNN estimates the throttle and steering angle, and if any obstacles are detected by sensors, the Fuzzy Logic Controller makes decisions based on fuzzy sets and the fuzzy inference system to avoid obstacles. The CNN continues to estimate the throttle and steering angle while the Fuzzy Logic Controller modifies the steering angle or adjusts speed to avoid obstacles.

The detailed operations of main units of the logic are:

A. Deep Neural Network

CNN has shown excellent results in image recognition and self-driving vehicles. CNN predicts throttle and steering angle, with data augmentation used for better performance. The CNN model used in self-driving vehicles typically includes five linked convolution layers, with angle division and activation functions used for steering and throttle.

B. Fuzzy Inference system

The Fuzzy Logic Controller has three parts: Fuzzification unit, Inference system, and Defuzzification unit. The input data is converted into fuzzy data, IF-then rules are applied, and the output is generated and converted into precise output. Two fuzzy logic controllers are designed based on the behavior of obstacles. The fuzzification unit receives precise (crisp) input values from sensors, such as the distance between a robot and an obstacle. It converts these numerical values into fuzzy linguistic variables. For example, a measured distance of **25 cm** may be represented as "Near" (0.8) and "Medium" (0.2). The output from the inference system is still in fuzzy form (e.g., Slow, Medium, Fast). The defuzzification unit converts this fuzzy result into a precise numerical value that can be used by the system. For example, the fuzzy output "Slow" may be converted into a motor speed of 15 cm/s or a steering angle

Table-1:Fuzzy sets for steering Angle

S no.	Angle		Value		Input/output Angle
	Min.	Max.	Min.	Max.	
1	-45.0	-22.5	-1.0	-0.5	Deep Left
2	-31.5	-4.5	-0.7	-0.1	Medium Left
3	-13.5	13.5	-0.3	0.3	Centre
4	31.5	4.5	0.7	0.1	Medium Right
5	22.5	45.0	0.5	1.0	Deep Right

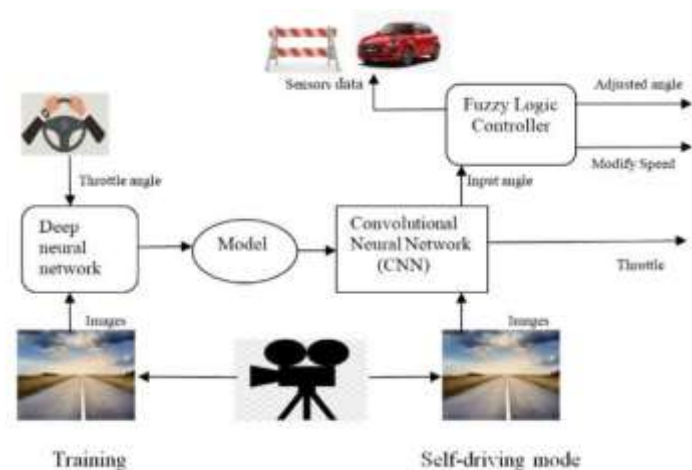


Figure-1: Modified Architecture of Obstacle Avoidance System

Being simple and instinctive rule bases the Mamdani inference system is easier to understand and suitable for human knowledge-based application.

Fuzzy Logic Controller for Stationary Obstacles:

In this controller four inputs are taken; first is the current steering angle from CNN and the rest of three are distances to obstacles from left, center

and right ultrasonic sensors. The output of the controller is modified steering angle. All the linguistic variable and fuzzy sets of input and output steering angle are shown in Table 1.

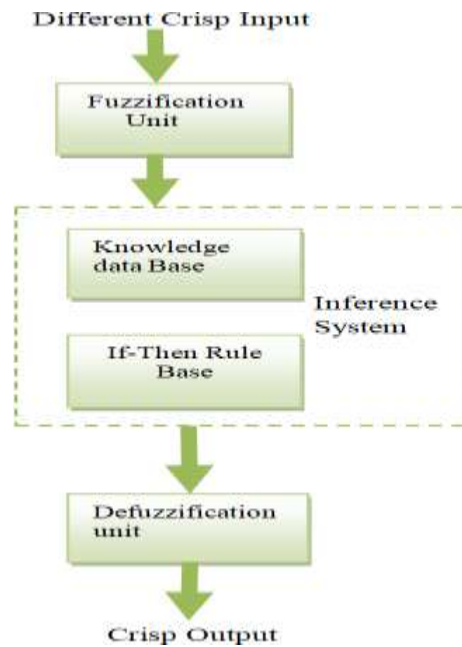


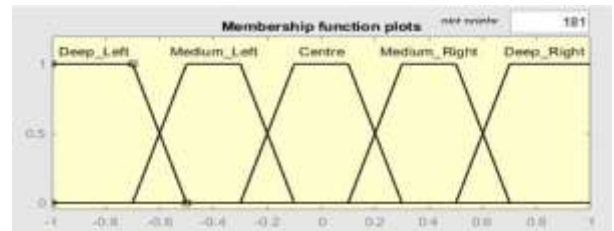
Figure-2: Basic structure of Fuzzy Logic Controller

To explain Input and output steering angle, 5 membership functions as shown in table 1 are used: Deep left, medium left, centre, medium right and deep right. Linguistic variable and fuzzy parameter for other three distances inputs are shown in Table 2.

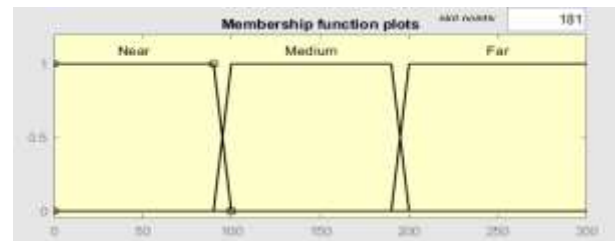
Table-2 Fuzzy sets for distance

S. No.	Input	Left Distance	Centre Distance	Right Distance
1	Near	0-100	0-100	0-100
2	Medium	90-200	90-200	90-200
3	Far	>190	>190	>190

Trapezoidal membership functions are applied for input and output variable which are shown in figure 3.



(A)



(B)

Figure-3. Membership function for (A) Input/output steering angle (B) Input Left, center and right distances to obstacles.

There are 39 If-then rules for obstacle avoidance in self-driving vehicles, set by experienced experts. Some rules include adjusting steering angle based on the angles and distances detected by the vehicle's sensors. For example, if the input angle is far left and center distance is near with far-right distance, the output steering angle should be medium right. If the input angle is center with far left and front distances and medium right distance to the right, no modification to the output angle is needed. If the input angle is medium right with near left and center distances and far right distance, the output steering angle should be deep right. These rules help the SDV navigate in varying environments. The defuzzification of the output steering angle is calculated by center of area (COA) method.

Fuzzy Logic Controller for Moving Obstacles:

Avoiding moving obstacles is a complex task for self-driving vehicles as it requires adjusting both

speed and steering angle. The controller is designed for ideal conditions where all obstacles and the vehicle are moving in the same direction. The inputs are front and right distances to the obstacle and change in distance to the front obstacle, while the outputs are adjusted steering angle and modified speed. Fuzzy sets and linguistic variables are used for input and output variables.

Table-3:Fuzzy sets for Modify speed

S No	Output	Speed value
1	Zero	0
2	Very slow	>20
3	Slow	20-30
4	Medium	30-60
5	Fast	60-100

Fuzzy sets and linguistic variable for input to variable distance obstacle is same as for stationary obstacles and for output variable is shown in Table 3. The if-then rules for obstacle avoidance in self-driving vehicles are based on the expertise and experience of human drivers and engineers. These rules provide a set of guidelines that the self-driving vehicle's control system can use to make decisions about how to respond to different scenarios. The rules take into account the front and right distances to obstacles as well as the change in the distance to the front obstacle. Based on these inputs, the rules determine the appropriate adjusted steering angle and modify speed for the self-driving vehicle.

It's worth noting that these rules are not exhaustive and may not cover all possible scenarios. Therefore, the control system may need to incorporate additional rules or use more sophisticated techniques to handle complex situations. Nonetheless, the If-then rules provide a useful starting point for designing an obstacle avoidance system for self-driving vehicles.

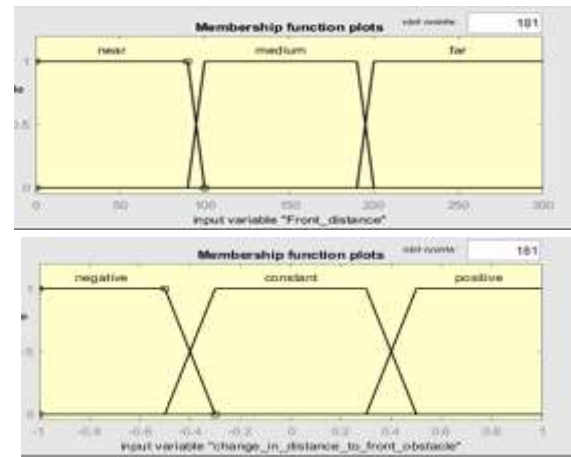
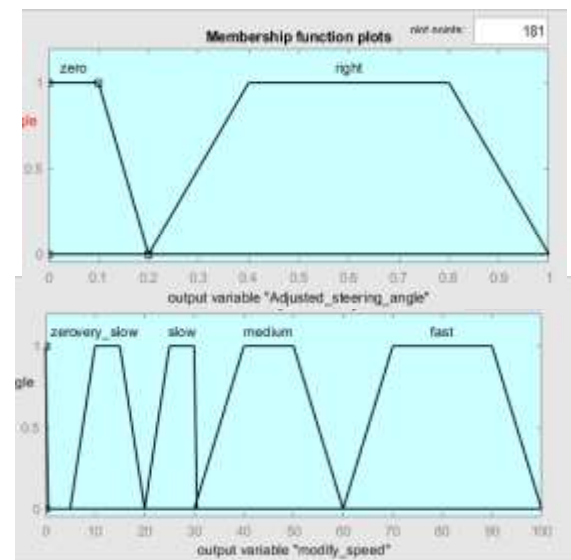


Figure-4:Membership function for (A) Input front distance to obstacle and right distance to obstacle (B) Input change in distance to front obstacle.



(B)

Figure-5:Membership function for (A) Output adjusted steering angle (B) Output change Modify Speed

IV. SIMULATION SETUP AND DEVELOPMENT

The V-REP software is used for virtual robot experimentation and MATLAB is used as a remote API client for the fuzzy logic controller. Three ultrasonic sensors and a large view camera are used for obstacle detection and avoidance.

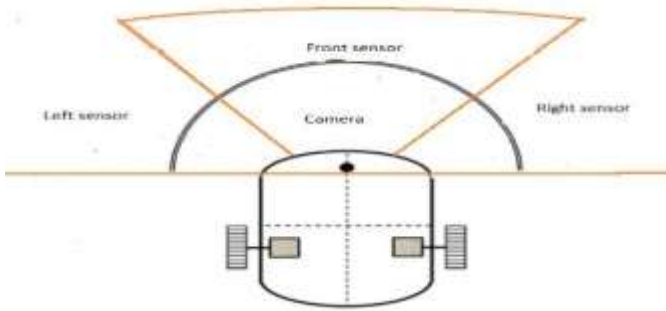


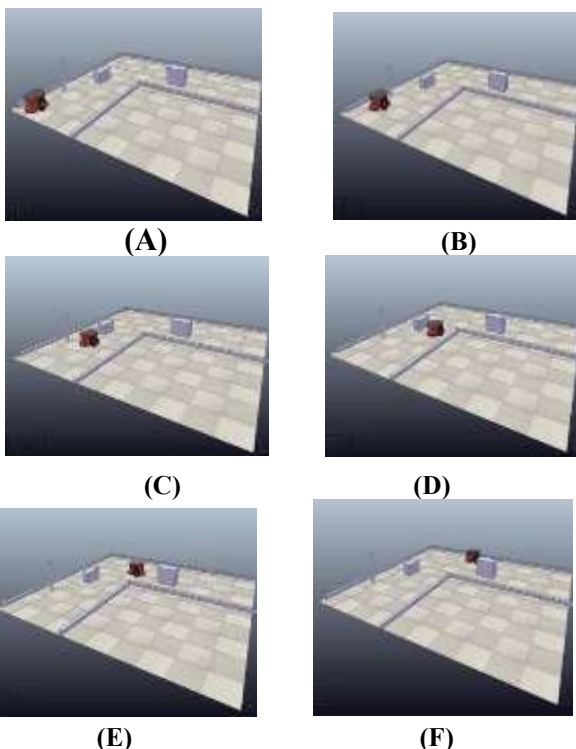
Figure-6:Sensors position in self-driving vehicle

V. RESULT AND DISCUSSION

The simulation result is evaluated based on how quickly the self-driving vehicle makes the decision to avoid the obstacle.

Simulation Result in case of Stationary Obstacle:

Navigation around stationary obstacles is shown in Figure 7.



(G)

Figure-7:Navigation around stationary obstacles (A) Simulation environment (B) Approaching first obstacle (C) Adjust steering right to avoid first obstacle and approaching second obstacle (D) Steer right to avoid second obstacle (E) Approaching third obstacle (F) Steer left to avoid third obstacle (G) Finally, the vehicle continues its path.

The result is evaluated on the basis of how quickly the vehicle makes the decision to avoid the obstacle and is shown in Table 7.

Table-7:Simulation Result

Obstacle	First	Second	Third	Result
Time to make decision	5 second	3 second	4 Second	Successful

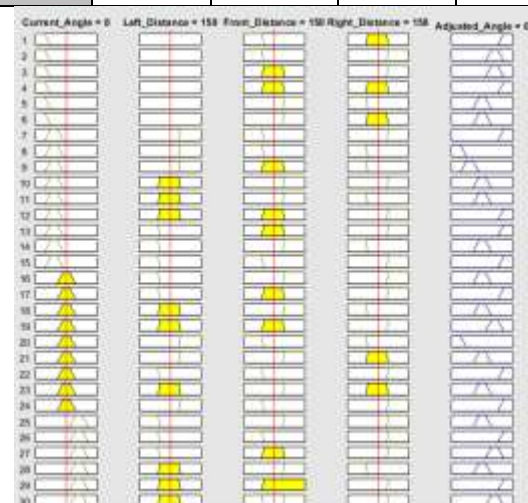


Figure-8:Rule Viewer in case of Stationary obstacles

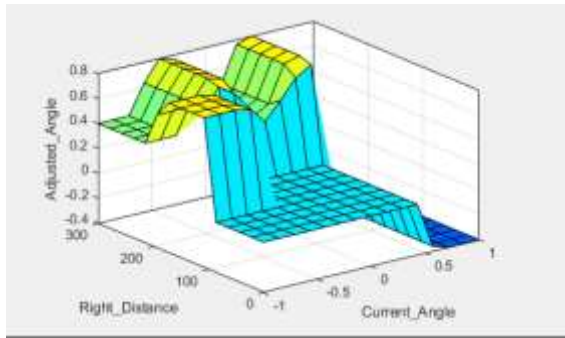


Figure-9:Surface view with respect to Adjusted angle

Simulation Result in case of Moving Obstacle:

As the controller is designed for the ideal environment and for right-hand driving, so only right-side overtaking is supposed to be allowed. Although the controller is also adapted for left- hand driving. For moving obstacles various types of vehicles are used, which are moving with constant speed in the same direction of self- driving vehicle. Navigation around moving obstacles is shown in Figure 10.



(A)



(B)



(C)



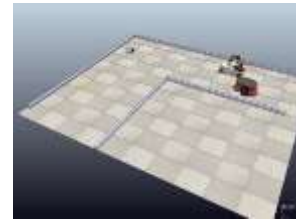
(D)



(E)



(F)



(G)

Figure-10:Navigation around moving obstacles

(a) Simulation environment (b) Approaching first obstacle (c) Adjust steering right and accelerate to avoid first obstacle (d) moving as no obstacle around (e) Approaching second obstacle (f) Steer right and accelerate to avoid third obstacle (g) Finally, the vehicle continue its path.

The result is evaluated on the basis of how quickly the vehicle makes the decision to avoid the obstacle and is shown in Table 8.

Table-8:Simulation Result

Obstacle	First	Second	Result
Time to make decision	3 second	4 second	successful



Figure-11:Rule Viewer in case of Moving obstacles

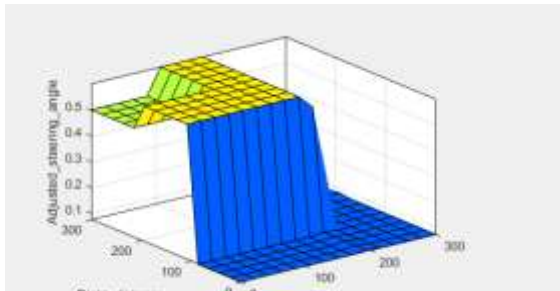


Figure-12: Surface view with respect to Adjusted angle

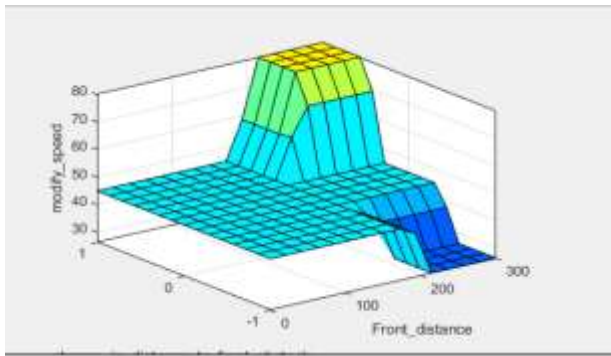


Figure-13: Surface view with respect to Modifyspeed

VI. CONCLUSION

Our proposed work discusses the design of fuzzy logic controllers for navigating self-driving vehicles in environments with stationary and moving obstacles. The controllers are rule-based and adaptive to varying obstacle sizes, and incorporate data from sensors and CNNs. Simulation results show promise for future use. However, further work will include designing controllers for varying speeds of moving obstacles and increasing the number of sensors for multi-vehicle environments to enhance the performance of the vehicle.

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