Fuzzy Logic Based Collision Avoidance System For Autonomous Navigation Vehicle

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Abstract— In order to decrease the accidental traffic in the real world, many kinds of research in the advanced driver-assistance systems (ADAS) programs have been made. Pre-defined path tracking with obstacle avoidance is one of them and hasn't been fully automated yet. In this paper, a fuzzy logic controller approach is proposed for collision avoidance safety system (CAS) with self-driving vehicle navigation control. The navigation controller gives the desired tires angle to keep our vehicle on right track till reaching goal point while processing the 2D laser information in case of obstacle or pedestrian detection leading to safety maneuvering or suddenly stop. Experimental work was performed on GAZEBO simulation tool and the controller was designed and implemented on MATLAB Simulink. The results show that the controller provides a significant improvement in decision making while navigation.

Keywords—ADAS, Fuzzy Control, Collision Avoidance System, Autonomous Navigation System.

I. INTRODUCTION

The evolution of the Advanced Driver Assistance Systems (ADAS) during the past decade becomes a global area of research to prevent frequently mistakable accidents [1]. ADAS technology used two categories of built-in sensors, the Proprioceptive sensors, and Exteroceptive sensors.

First: is the Proprioceptive sensors which are based on (Encoder, Gyroscope and GPS), this sensing category is utilized to provide the controller with the actual behavior of the autonomous vehicles, for example, an onboard Digital Global Positioning System (DGPS), unified with an Extended Kalman Filter (EKF) for noise filtration [2]. Whereas in [3-5], they employed the strategy of combining the GPS and Inertial Navigation Systems (INS) sensors for more accuracy. The INS produce unknown biased signals that provide the position error by integrating the acceleration values. While the GPS role is to produce accurate drift positioning location; this value is yielded to reset the INS output. The gain behind using this fusion, is the INS offer more frequent and quicker position and angle updates to be reused by the vehicle controllers, rather than operating the GPS alone[5]. Blending the GPS and INS with Kalman filter helps in case of satellite, outage happens occasionally. Furthermore, integrating the Odometry to the system with INS produces the ultimate accurate position and angle even in the absence of satellite signals[6]. Second: is the Exteroceptive sensors which are founded on (Camera, LIDAR, Radar, etc.,), as Mendez et al. [7] used the Camera to detect the lane painting lines by vision computer approach, which defines the lane path to be followed accurately. Another technique by Cherubini et al. [8] uses the SICK laser to detect the road rows and landmarks, by calculating the laser point and processing it. Afterward, it distinguishes between the targets and the noises. Consequently, achieving an accurate path.

The working principle of the ADAS controller is that it analyzes the coming data from the sensor and produce a certain output to ensure a safe driving. Many collision avoidance algorithms have been developed since the last decade. These algorithms have improved the navigation through the moving obstacles. This is done by combining the obstacles moving characteristics and the road structure. This technique will guarantee an accurate trajectory prediction [9]. While in [10], the human driver's experience is translated into a rough set. Also, the acceleration and deceleration values were inspected and controlled while lane maneuvering. A different research in [11] used the GPS signals among urban vehicles by connecting it with the controller, using the laser sensor for pedestrian detection. This technique enables possible collision detection while doing the road intersection, subsequently, gives better results. A group of studies [12, 13] suggested that calculating the distance between vehicles and obstacle can be used to predict the collision better, then decide whether to maneuver or decelerate within the lane boundary. While, for Simultaneous Localization And Mapping (SLAM), Valencia et al. [14] build a map free of obstacles between the goal and the starting point. Lastly, the experiment shows an improvement in navigation.

Another method is the Vector Field Histogram (VFH), which is widely spread among manned and unmanned autonomous vehicle navigation systems. This approach works by calculating the angle and the probabilities of the nearest obstacles' distances during path planning. Next, the controller initiates a path free from these obstacles. The controllers commonly used is PID. While the sensors can be: DGPS, or 3D, or LIDAR [15].

Whereas, the global algorithm used in Unmanned Surface Vehicle (USV) is an Artificial Potential Field-Ant Colony Optimization (APF-ACO). It worked by using the LIDAR data processed by the fuzzy logic algorithm, to produce the required steering maneuvering [16]. Another strategy is combining the Day Light Camera (DLC), uncooled infrared camera, and the Laser Range Finder (LRF). That gives superior marine ship detection and avoidance results [17]. Searching algorithm is correspondingly used to calculate the collision-free path between Autonomous Search Vehicle (ASV) and waypoint —ASV depends on colored cameras. These techniques ensure a flexible maneuvering swap between obstacles [18, 19]. While for gaining low-speed obstacle avoidance, a unique approach [20] was employed, it depends on the degree of collision risk to active the barrier function controller. This is done by using the polar algorithm combined with the barrier function.

Fuzzy logic is also remarkable in ASV, as [21] calculates the collision risk degree to avoid obstacles for unmanned roads. Besides, fuzzy logic harnesses speed, distance and road condition (wet or dry) to produce a suitable brake action [22]. Even more, fuzzy logic fused with Kalman filter are yielded to predict the pedestrian location, so to avoid any collision possible with rules defined possible actions [23]. While [24] takes into account the nonholonomic constraints and guarantees global convergence of the position and orientation coordinates, to reduce position and orientation errors. A different method is based on the concept of the minimum cost function. It depends on sensors like 2D LIDAR to get the information about obstacle location. After that, it produces output signals like speed and angle [25]. Fuzzy logic weight controller is also used when many obstacles are in the scene while navigating to the waypoint, this produces path planning free from obstacles like human expert [26, 27].

Another study uses multiple inputs multiple output fuzzy algorithm for speed and steering control, this approach aims to safe delivery to the target point [28]. While in [29], navigation using laser scanner ranges to detect obstacles by a fuzzy logic algorithm to reach the goal point.

In general, real-world testing scenarios are costly, i.e., sensor and actuators of ADAS are expensive. Therefore, a powerful simulation tool as GAZEBO simulator is required. This open source software can be interfaced with the MATLAB program, through the Robotic Operating System (ROS) [30-32].

In this study, an intelligent ADAS system is proposed, which is based on autonomous CAS. It consists of: (1) Multi-Input Multi-Output fuzzy logic controllers one for collision avoidance (CAC) and the other is the weighting controller (W). (2) trajectory geometry controller (TGC) for vehicle navigation, to navigate the vehicle even in the presence of obstacles. The master fuzzy controller gives an order to (CAC) or (TGC). This algorithm is provided to keep the vehicle tuned with the environmental risks. The fuzzy controllers and Robotics Operating System (ROS) communication were designed on MATLAB Simulink. While the virtual urban was built-in simulation environment, intended for developing the ADAS during the navigation.

The paper is divided as follows. Section A: Related work. Section II: The Model architecture based on MIMO data. Section III: The proposed fuzzy controller architecture. Section IV: Results and Experiments. Section V: Conclusion. And finally, Section VI: Future works and area of development.

A. *Related work*

When Applying the VFH as in [33, 34] on a real vehicle for CAS, by using Velodyne 3D LIDAR Sensor and GNSS for global path planning, with PID controller [15], the results show a real vehicle go through predefined map collected by real-time kinematic- global navigation satellite system RTK-GNSS formed with a large number of traffic cones, while LIDAR work to get colored ranges to point cloud to the VFH controller, which updates the local path planning with a free obstacle path, through multiple obstacles which guide self-driving PID controller.

II. Model Architecture

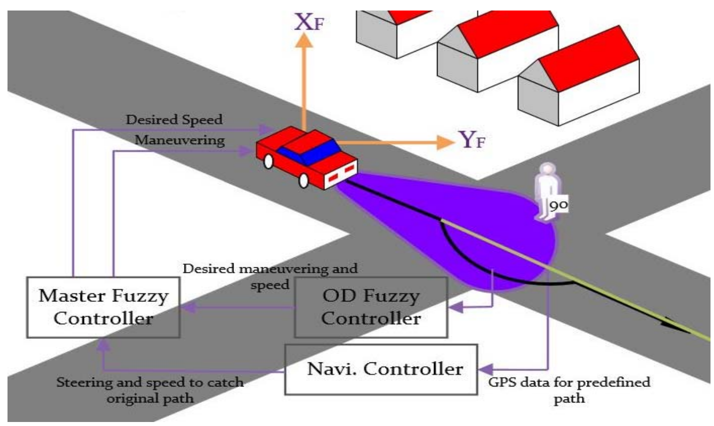

Figure 1 Model Architecture

As any ADAS system containing I/P, O/P and controlling system, the paper proposes a MIMO fuzzy logic controllers for decision making, based on [26, 27], and GPS/INS/Odometer sensor [4] for Integration between the Global Positioning System (GPS) and Inertial Navigation Systems (INS). While using the SICK 2D Laser scanner for obstacle avoidance, and keeping the vehicle in the right track as shown in *Figure 1*

After estimating the vehicle location by two GPS/INS/OD [3-6, 35] information, now an accurate (x, y, heading) is available, then to track predefine path a TGC requires (x, y) for each point in that path, and orientation to reach that point along, this controller developed by Hoffmann in Stanley —The Robot that Won the DARPA Grand Challenge shown in *Figure 2*, is based on a nonlinear feedback function of the cross-track error, The angle α describes the orientation of the nearest path, the e represents the linear error. The larger this error, the stronger the steering response towards the trajectory by angle.

$$\beta(t) = \beta(e, u, \alpha) = \alpha(t) + \arctan\frac{ke(t)}{v(t)} \tag{1}$$

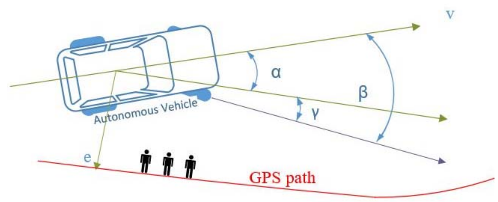

Figure 2 Wheel Angle Estimation to keep the vehicle on the desired path

A. *Proposed Fuzzy Controller*

This research contribution is manifested by adding two fuzzy controllers, instead of the VHF for a free road of collision decision making. The first fuzzy controller (CAC) [28] using the information will come from the laser sensor, attached in front of the vehicle, this controller will work only in case of collision detection by processing two emergency inputs, Obstacle Distance (OD) and Corresponding Angle (CA), named (laser points). The laser sensor has a wide angle of 180 degrees and an 80 m distance range. The paper is interested only in the narrow-angle readings correspondence to vehicle width, no need for gathering all environmental info as that will lead to controller distortion when an obstacle comes in the vehicle sphere, then the fuzzy logic controller will take the lead to decide the action via certain rules and membership functions.

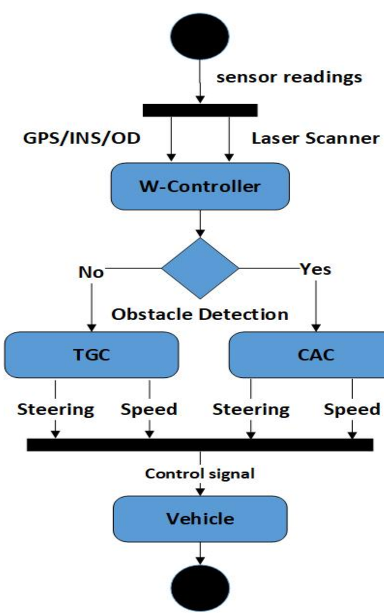

Figure 3 Schematic Fuzzy Controller Diagram

The second fuzzy controller (W) is inspired from [26, 27], this controller will act as decision makers to decide which state the vehicle will follow, whether the TGC or CAC controller this decision based on the risk weight of the value originated from the CAC controller, if obstacle is shown in the scene the largest value will be taken from CAC, and vice versa from TGC when there is no obstacle, see *Figure 3.*

B. *Fuzzy Membership function*

The first Controller CAC will have fuzzy inference system with two inputs two output linguistic variable. Inputs are (a) Left and right vehicle center lines, (b) The distance between the vehicle and the forward-facing obstacle detected by the SICK laser sensor messages. Outputs are the steering maneuvering and the safe speed. The fuzzy controller used a 4 trapezoidal and 14 triangles membership function to graphically shaped the fuzzy set as shown in TABLE I.

TABLE I. COLLISION AVOIDANCE FUZZY VARIABLES

CAC Membership Function			
Variable		***Membership Function***	
Input	Obstacle Distance (OD)	Close Med Far	Trapmf [0 0 3 4] Trimf [0 0 3 4] Trapmf [5 6 9.5 10]
	Obstacle Angle (OA)	Far-Left Med-Left Close-Left Close-Right Med-Right Far-Right	Trimf [0 2.7 5.2] Trimf [1.8 5.2 8] Trimf [6 8.4 10.6] Trimf [9.4 12 15] Trimf [10.8 14 17] Trimf [15 19.5 20]
Output	Safe Speed (SS)	V-Slow Slow Med	Trimf [0 0.73 1.5] Trimf [1 1.9 2.8] Trimf [2 3 4]
	Steering Maneuvering (SM)	VB-Right B-Right Right Left B-Left VB-Left	Trapmf [-2 -2 -1.5 -1] Trimf [-1.4 -1.2 -0.6] Trimf [-0.75 -0.4 -0] Trimf [0.2 0.5 1] Trimf [0.5 1 1.4] Trapmf [1 1.5 2 2]

The second Controller (W) will have a fuzzy inference system with two inputs and one output linguistic variables. Inputs are path error distance to the nearest point on the GPS path and obstacle distance to any obstacle shown in front of the vehicle. Whereas the output is the weight factor from 0 to 1, see TABLE II, it acts as a master controller that take the decision which controller will work. While, the weight depends on the shown obstacles in the scene, corresponding to the following equations.

$$Speed = (PD * W) + (OD * (1 - W)) \tag{2}$$

$$Steering = (PA * W) + (OA * (1 - W)) \tag{3}$$

TABLE II. WEIGHT CONTROLLER FUZZY VARIABLE

Switching State Membership Function			
Variable		***Membership Function***	
Input	Path Error Distance	Near Med Far	Trimf [0 0 0.6 1] Trimf [0.5 2 4] Trimf [3 6.5 10]
	Obstacle Distance(OD)	Nera Med Far Out	Trapmf [0 0 2 4] Trimf [3 4.5 6] Trapmf [4 6 7 8.9] Trapmf [4 6 7 8.9]
Output	Wight (W)	Nera Med Big VBig	Trimf [-0.1 0 0.1] Trimf [0 0.2 0.4] Trimf [0.2 0.4 0.6] Trapmf [0.4 0.7 1 1]

C. *Fuzzy Rules*

Fuzzy Associative Memory (MAM) constructed as two Fuzzy rules categories inspired from [26]. The first group for the (CAC), this rule is based on three distance linguistic variable and six obstacle angle variables. This combination produced 18 rules, gathering all possible action required for any sudden situation faces the vehicle in its trip, whether to make steer maneuvering or speed slow down as shown in TABLE III.

TABLE III. CAC FUZZY RULES

Rule	Inputs		Output	
	OD	***OA***	***SS***	***SM***
1	Far	Far Left	Med	Right
2	Far	Med Left	Med	Big Right
3	Far	Close Left	Med	VB Right
4	Far	Close Right	Med	VB Left
5	Far	Med Right	Med	B Left
6	Far	Far Right	Med	Left
7	Med	Far Left	Slow	Right
8	Med	Med Left	Slow	B Right
9	Med	Close Left	Slow	VB Right
10	Med	Close Right	Slow	VB Left
11	Med	Med Right	Slow	B Left
12	Med	Far Right	Slow	Left
13	Close	Far Left	V Slow	Right
14	Close	Med Left	V Slow	B Right
15	Close	Close Left	V Slow	VB Right
16	Close	Close Right	V Slow	VB Left
17	Close	Med Right	V Slow	B Left
18	Close	Far Right	V Slow	Left

The second 12 fuzzy rules group decide the weight factor (W) that will substitute in Eq. (2) and Eq. (3). They depend on whether the obstacle is in the scene or not, and its distance accordingly to our vehicle which called obstacle distance (OD), with taken into consideration the distance to reference GPS path for leading distance (LD), to give one of our controller the upper hand (TGC) or (CAC), with respect to the other, that’s mean minimum path deviation, even in the presence of an obstacle in the scene see TABLE IV.

TABLE IV. WEIGHT CONTROLLER (W)

Rule	Inputs		Output
	LD	***OD***	***W***
1	Far	Out	VBig
2	Far	Far	Big
3	Far	Med	Med
4	Far	Close	Small
5	Med	Out	VBig
6	Med	Far	Big
7	Med	Med	Med
8	Med	Close	Small
9	Near	Out	VBig
10	Near	Far	Big
11	Near	Med	Med
12	Near	Close	Small

III. EXPERIMENTS AND RESULTS

A. *Gazebo Simulator and MATLAB*

In order to observe the proposed algorithm behavior response, a virtual simulation tool was used, the model was built by GAZEBO simulator, it's an open source program used for testing autonomous algorithms, designs, perform complex testing and train AI systems. Gazebo offers the ability to accurately and efficiently simulate populations of an autonomous vehicle in complex environments. It also provides a set of (ROS) application program interface (API's) that allows users to modify and get information about various aspects of the simulated world.

ROS is a robot framework establishing the communication channel between vehicle and MATLAB controller, ROS provides nodes which is a process that performs computation, for example, one node controls a steering angle, one node controlling laser scan messages, one node controlling location. Nodes exchange messages through the topic. Topics is a bus produce information from nodes to publish/subscribe data, shows nodes and topics running on the CAT-vehicle model. While the Fuzzy model controller Developed on the MATLAB robotic operating system toolbox, acquiring the node data which come from the GAZEBO into input subscription and output publishing topics as shown in *Figure 4.*

B. *Experimental Setup*

The Experiment was built by GAZEBO environment, on ROS Indigo VM. The CAT vehicle was added by SICK laser LMS291, with 80 meters and 180 angle degree range, besides SPAN-CPT GPS/INS sensors it was developed by the University of Arizona, they won DAPRA grand challenge 2006, and built an environment paved with road bordered by jersey barriers along the entire lane, with presence of suddenly pedestrian front of the vehicle. In this research, a linear direction was assumed for the pedestrian movement towards the vehicle path as shown in *Figure 5.*

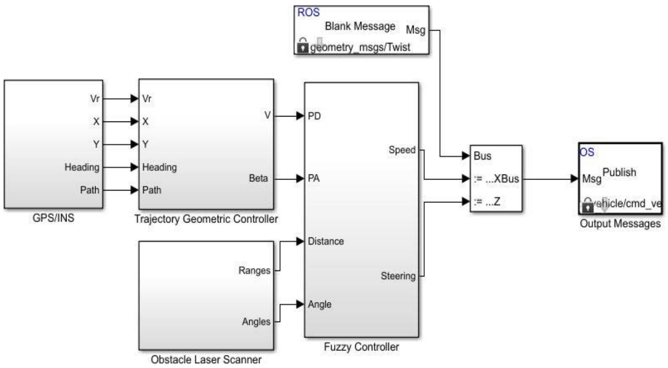

Figure 4 Simulink CAC ModelSimulation Test without obstacles

The environment was paved by single road with jersey barriers at borders, the vehicle starts with 3 m/s speed at -0.15 m away from the reference path, the weight controller gives big weight to TGC as an input signal to produce left steering control, till catch the GPS path after 8 meters, in order to govern the vehicle on the track to end of trip as shown in *Figure 6* the red line illustrated the GPS received path, while the blue represents the actual path of the vehicle. The experiment shows that the Simulink model responded very quickly to the reference path signal received from GPS during navigation.

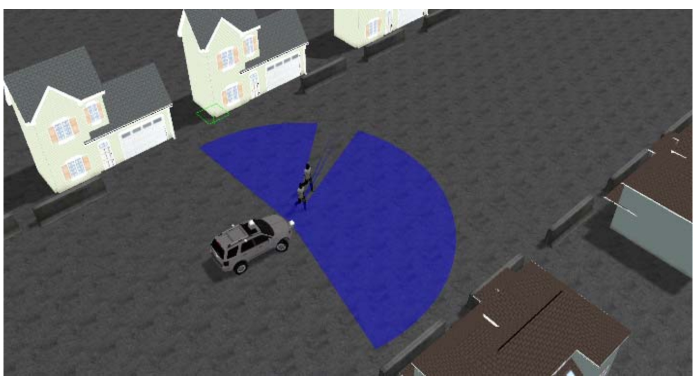

Figure 5 Experiment Environment Using GAZEBO platform

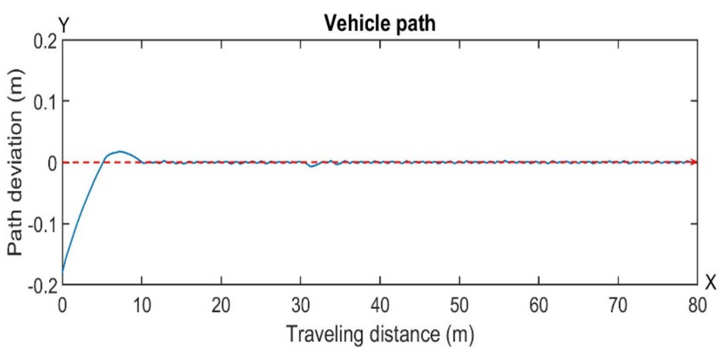

Figure 6 vehicle Reference path and the actual path

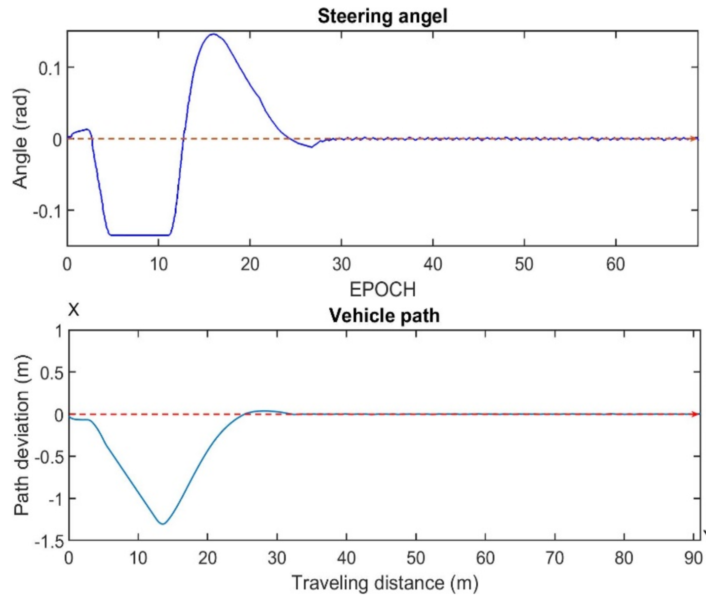

Figure 7 vehicle maneuvering angle and path deviation during obstacle detection

C. Simulation Test With obstacles

This experiment was initiated to test the performance of the three controllers with predefine red path 200 meters long, the vehicle laser sensor detects an obstacle in the vehicle path by 15 degrees and 6-meter distance to the left center of the vehicle, the weight controller detects the obstacle and gives a big weigh value (T=0.9) to the (CAC). This controller produces the required steering and speed to do two things, a safety maneuver by 20 degrees, and angle to the right to avoid the collision as a human decision with decreasing speed to 3 m/s.

After safe maneuvering blue path, the W controller sends a big weight to the (TGC) to raise the vehicle speed from 3 to 10 m/s and a 10-degree steering to the left till reaching the GPS red path as shown in *Figure 7.*

IV. CONCLUSION

Fuzzy Logic Controllers provides more flexibility and fast response with minimal errors, despite many different sensor data inputs come from the environment like human do, the using of GPS/INS/OD for vehicle navigation controller (TGC) proves the capability to adapt the vehicle speed and steering very smoothly. While the (CAC) controller keeps ready on the spot if any obstacle shown suddenly in front of the vehicle. This is done by using a very accurate SICK laser message, the (W) controller shows a fast response when giving the upper hand for the right controller, depending on the present situation.

In essence, this research developed a fuzzy multilayer controller to adapt the collision avoidance in a straight road, a future work is to tune the controller with the roundabouts and curves road factors, consequently, improving the steering control in that scenario.

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