Fuzzy Logic Controller for Controlling a Mobile Robot with Obstacle avoidance behaviour

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***Abstract*—This paper describes the design and simulation of a Fuzzy Logic Controller (FLC) for controlling a mobile robot with obstacle avoidance behavior in indoor environments. The FLC takes three inputs from the readings of nine ultrasonic sensors, and two outputs to generate a voltage value for each of the two wheel motor. The FLC was designed in Fuzzy logic toolbox of MATLAB and simulated in V-REP.**

Keywords*—*Fuzzy Logic Controller, Obstacle Avoidance, Mamdani fuzzy, Mobile robot.

I. Introduction

Autonomous mobile robots have many applications in fields such as industry, transportation, military, etc. The importance of developing a navigation controlling system is increasing over the last two decades, therefore, intelligent mobile robots are needed to perform autonomous navigation and obstacle avoidance in unknown cluttered environments. One of the various techniques used in mobile robotics is Fuzzy logic, which provides a solution to handle imprecise information and integrate the human reasoning.

In this paper, a Fuzzy Logic Controller was designed to control a mobile robot with obstacle avoidance behaviour in indoor environments with static obstacles.

This paper is organized as follows: Section II presents the design and implementation of Fuzzy Logic Controller (FLC), Section III presents the design justification of the FLC, Section IV describes the performance of the controller, and lastly, in Section V a literature review of various application of fuzzy logic with intelligent algorithms and hybrid fuzzy systems are presented and discussed.

II. Design and Implementation

A. Fuzzy Logic Controller

A Fuzzy Logic Controller (FLC) was designed to control a mobile robot with obstacle avoidance behaviour in indoor environments. The FLC was implemented using Mamdani Fuzzy using three inputs namely FOD (Front Object Detector), LOD (Left Object Detector) and ROD (Right Object Detector). The value of the three inputs are in range from 0 to 1. Gaussian, triangular and trapezoidal type membership functions where used to define five fuzzy sets for each input, as very_near, near, medium, far, very_near.

The FLC provides two outputs, LM (Left Motor) and RM (Right Motor), each one for controlling the left and right wheel of the robot. The values of the two outputs are in range from 0 to 5 volts. The two outputs utilizes trapezoidal, Gaussian and triangular type membership functions, and three fuzzy sets with linguistic variables as high, low and medium. Figure 1 illustrates the workflow of the designed Fuzzy Logic Controller.

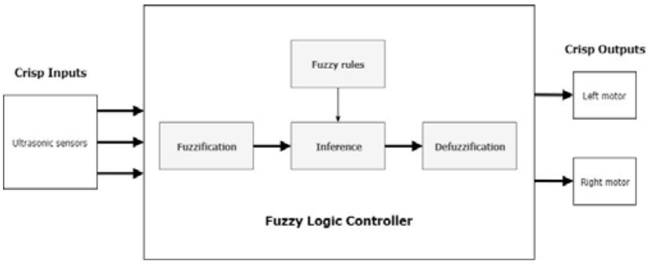

Fig. 1. Diagram of the FLC

B. Simulation

The performance of the Fuzzy Logic Controller was evaluated in a Pioneer 3DX mobile robot simulator in V-REP. Several simulations were performed to test the performance of the mobile robot in obstacle avoidance behaviour in an indoor environment with static obstacles.

Pioneer 3-DX developed by Active Media Robotics, is a mobile robot widely used for research in universities [1] since its release in 1995. Figure 2 shows a diagram of the Pioneer 3-DX. It comes with it has 16 built-in ultrasonic sensors with a sensitivity range from 10 centimetres to over 4 meters and two pneumatic tires controlled by two high-speed reversible-DC motors and a rear caster wheel to balance the robot. It reaches a max speed of 1.6 meters per second and has a capacity of carry a payload of up to 23 kg.

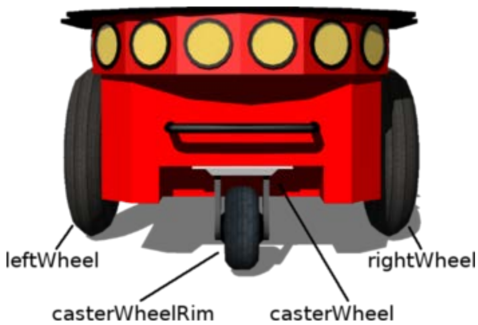

Fig. 2. Pioneer 3-DX. (Source [17])

Eight ultrasonic sensors are situated in the front of the robot, and another eight at the back and each side, each one with a 20° interval, providing 360° degrees of sensing range. See figure 3.

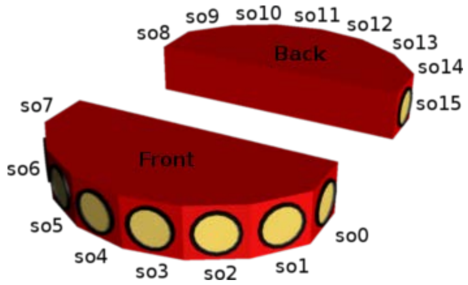

Fig. 3. Ultrasonic sensors positions. (Source [17])

For the experiments, only 9 ultrasonic sensors at the front of the robot where used as input for the Fuzzy Logic Controller. Three sensors located at forward of the robot (S2, S3 and S4) where used together as the FOD input for the Fuzzy Logic Controller, computing the minimal distance of the detected object by each sensor. The distance between the object and the robot was normalized as an interval from 0 to 1, being 1 the maximal distance detected by the sensor. Three more sensors were used as the LOD input (S0, S1 and S2) and ROD input (S5, S6 and S7).

The movement of the robot was controller by providing a voltage to the left and right motor, each one controlling the left and right wheel, respectively. The voltage provided ranged from 0 to 5 volts.

Braitenberg technique [2] was used for obstacle avoidance behaviour. The simulation was performed in V-REP PRO EDU Version 3.4.0 in a virtual environment of 5x5 meters, simulating an indoor environment with static obstacles. The Fuzzy Logic Controller was designed in Fuzzy Toolbox in MATLAB 2017a.

III. DESIGN JUSTIFICATION

A total of 30 fuzzy rules were designed to control the movement of the mobile robot. See Appendix 1. Tables 1 and 2 presents the values of the input parameters and outputs, respectively.

Trapezoidal membership functions were used to describe the Very_near and Very_far sets for the input variables FOD, LOD and ROD, due to the long range where they reach the maximum membership (a detected distance either too close or too far from the obstacle). Triangular membership functions were used to describe the Near and Far sets for the three input variables, due to their sloping gradient with a well-defined peak. A Gaussian membership function was used to describe the Medium set of the three inputs because of the smoothness in the peak which defines a less rigid membership. This will make the robot to smoothly identify an object from near, medium and far distance while it is moving. The range of the values of the membership functions were adjusted based on the longitude of the mobile robot when performing a turn. Figures 4, 5 and 6 shows the membership functions used for the three input variables.

Triangular membership functions were used to describe the Low and High sets for the two Output variables LM and RM. Triangular type was chosen because the drastically steep, which is required for the mobile robot to fuel its speed when perceiving a free path, or suddenly decrease the power in the motor at the presence of a near obstacle. A Gaussian membership function was used to describe the Medium set. Several evaluation were performed using different types of membership functions, where the Gaussian type delivered a smoother path during the navigation of the robot. These results were shared with [3]. Figure 7 and 8 shows the membership functions for the two outputs.

TABLE I. VALUES OF PARAMETERS FOR INPUTS

Membership function		***a***	***b***	***c***	***d***	
Very_near	trapezoidal	-0.33	-0.166	0.166	0.33	
Near	triangular	0.166	0.33	0.5		
Medium	Gaussian	0.5				0.05
Far	triangular	0.5	0.66	0.83		
Very_far	trapezoidal	0.66	0.83	1.167	1.33	

a. FOD, ROD, LOD input values

TABLE II. VALUES OF OUTPUTS

Membership function		***a***	***b***	***c***	***d***	
Low	triangular	-1	0	1		
Medium	Gaussian	2.5				0.75
High	triangular	4	5	6		

a. LM, RM output values

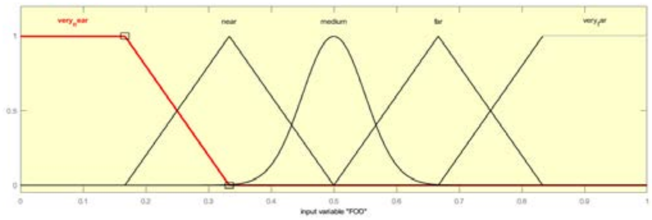

Fig. 4. Membership functions for input variable FOD

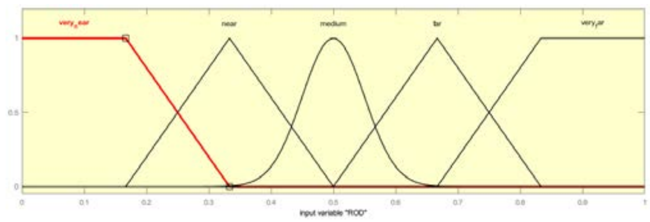

Fig. 5. Membership functions for input variable ROD

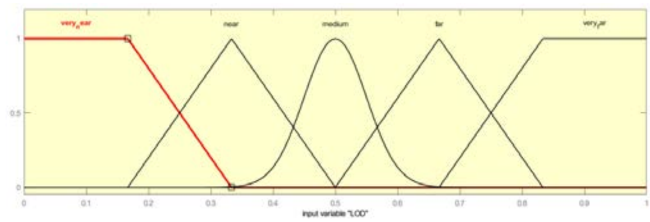

Fig. 6. Membership functions for input variable LOD

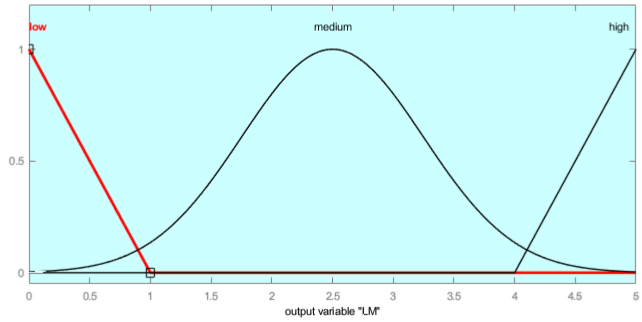

Fig. 7. Membership functions for output variable LM

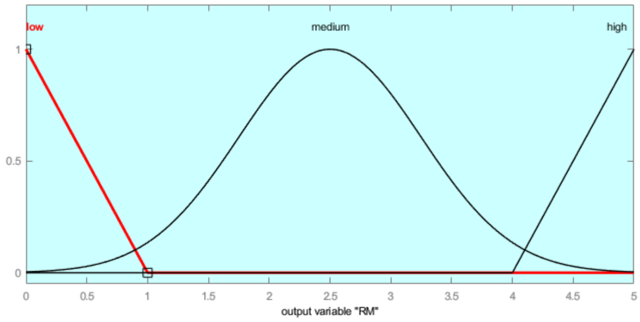

Fig. 8. Membership functions for output variable RM

The FLC was designed using Mamdani-type fuzzy inference. Although Sugeno-type fuzzy inference is more suitable for intelligent algorithms due to its less computing consumption compared with Mamdani-type [3,4], the last provides an overall smooth path, therefore Mamdani-type fuzzy inference was chosen for the FLC.

On situations when the robot encounters a u-shaped obstacle, dead end, or obstacles at its front, left and right side simultaneously, the mobile robot behaviour is designed to prefer to move to the right.

AND operation was used as product function and Centroid of Area method was chosen as the defuzzification method because it does not present variations when dealing with extreme values, as compared with other methods as Medium Of Maximum (MOM,) Large Of Maximum (LOM) and Small Of Maximum (SOM) [5,6].

IV. ANALYSIS OF THE CONTROLLER PERFORMANCE

Figure 9 illustrates the relationship between the Right Object Detector, Left Object Detector, and the Left Motor speed. It shows that the voltage provided to the left motor, hence the velocity of the left wheel of the robot, decreases as the obstacle gets closer, and it increases when the obstacle is either too far or out of range (no obstacles ahead). The FLC was designed in a way that the robot achieves its maximal velocity when it does not encounters obstacles in its path, and the velocity is drastically reduced as it is approaching an obstacle. This behaviour can be prove in the decision surface of the mentioned input variables and output value, where it shows that the right motor reaches its maximal value when an obstacle is far, as opposite than the left motor, which reaches its maximal velocity when the obstacle is near. This is because a less number of revolutions in the right wheel and higher number of revolutions in the left wheel will make the robot turn to the right, and vice versa for the left turn of the robot.

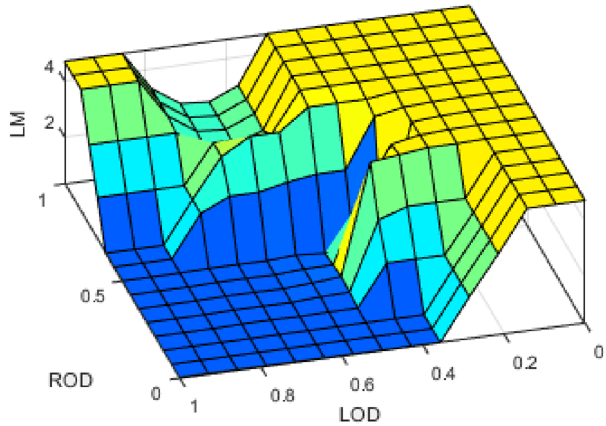

Fig. 9. Relationship between the right and left sensor, and the left motor.

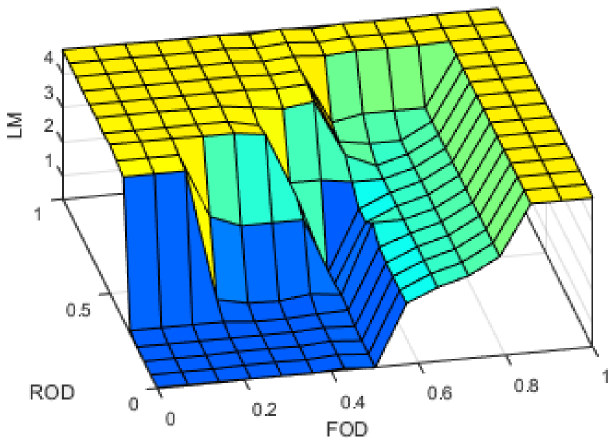

Fig. 10. Relationship between the front and right sensor, and the left motor.

Figure 10 illustrates the relationship between the Front Object Detector, Right Object Detector, and Left Motor. It shows that the speed on the left wheel of the mobile robot drops to 0 when the robot encounters an obstacle at a medium distance, this was designed so that the robot can have enough space to turn between its current position and the obstacle. The behaviour of the robot when encounters an obstacle at its front, is to prefer to move to its right, whenever there are no near obstacles, therefore, the left wheel is fuelled with high voltage while the right wheel power is decreased. This can be seen in the mentioned figure, where when the front and right sensor readings are small (obstacle is near at the front and right side of the robot), the power on the left wheel decreases at 0, and a further increment on the power of the right motor is provided, allowing the robot to turn to its left, as opposite to the obstacles.

Figure 11 illustrates the relationship between the front and right sensor reading inputs and the right motor speed. It shows that the voltage of the right motor is increased when an obstacle is detected at the front and right side of the motor, allowing the robot to turn to its left, avoiding the obstacles.

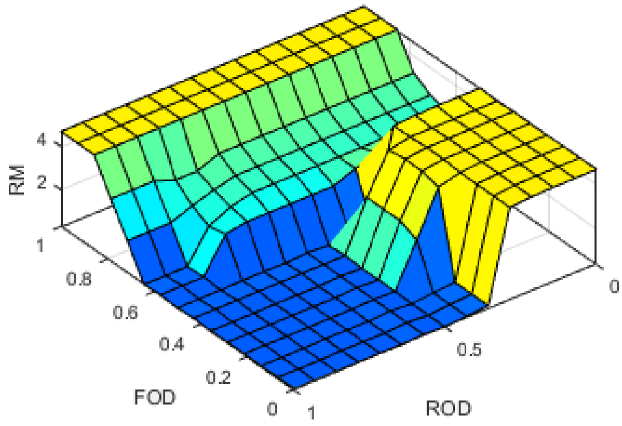

Fig. 11. Relationship between the front and right sensor, and the right motor.

Several simulations were performed to test the performance of the mobile robot. Three simulations are presented with 200 iterations each. Figure 12, 13, and 14 show the path navigated by the mobile robot in different starting points across the simulated environment, demonstrating the performance of the robot by successfully avoiding the obstacles. The output values for each simulation are presented in figures 15, 16 and 17.

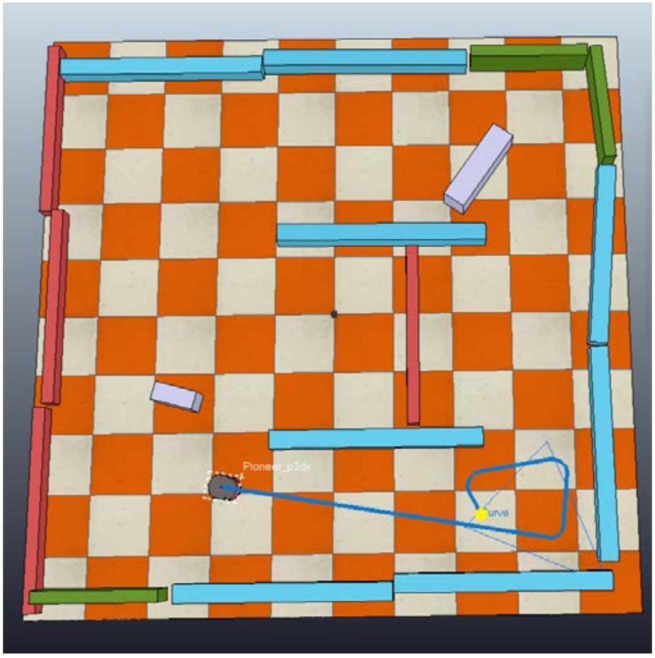

Fig. 12. Simulation 1

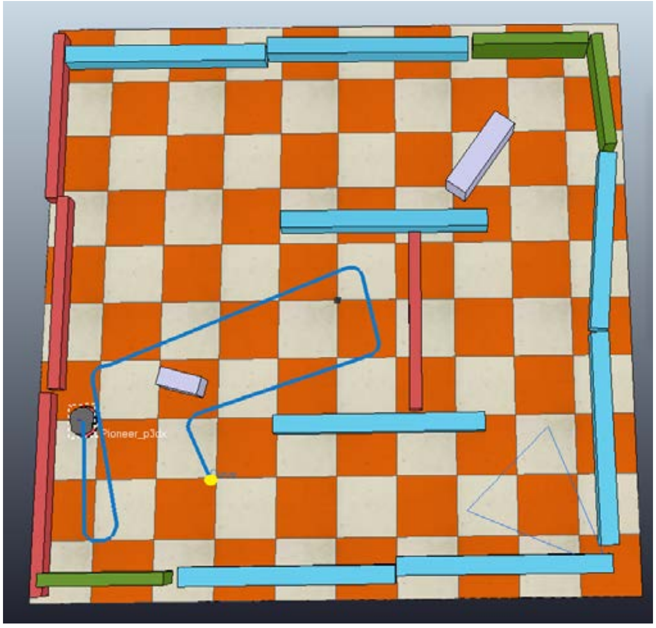

Fig. 13. Simulation 2

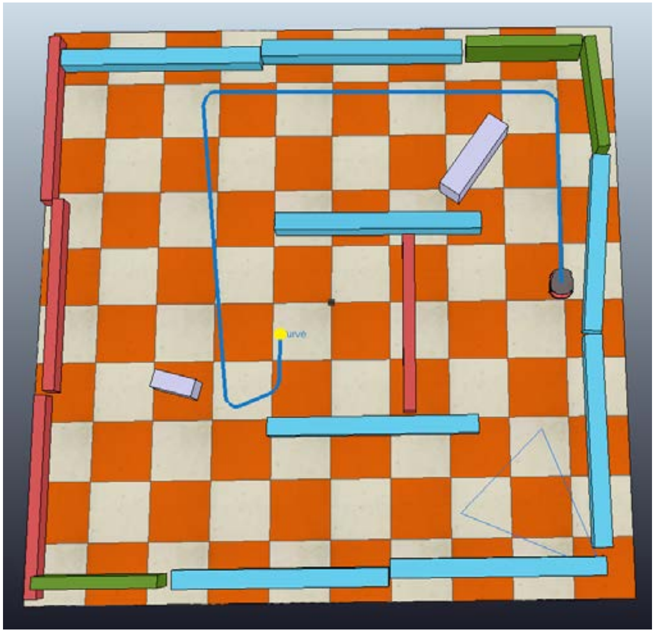

Fig. 14. Simulation 3

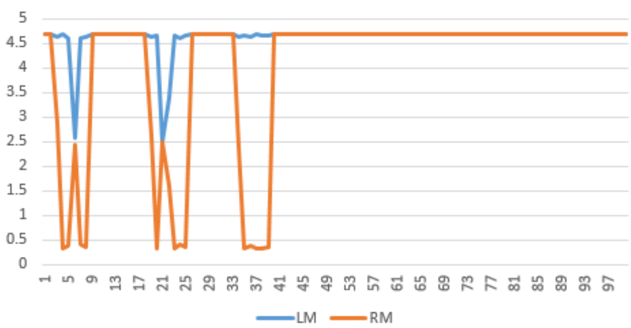

Fig. 15. Output values for Simulation 1

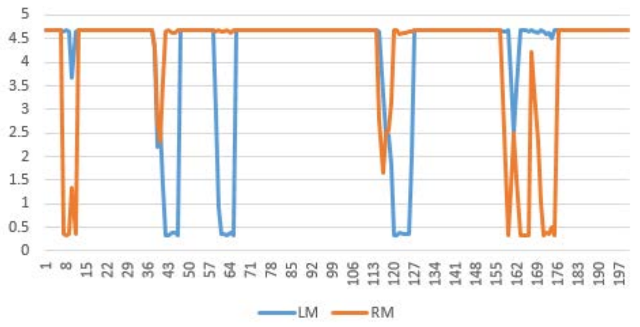

Fig. 16. Output values for Simulation 2

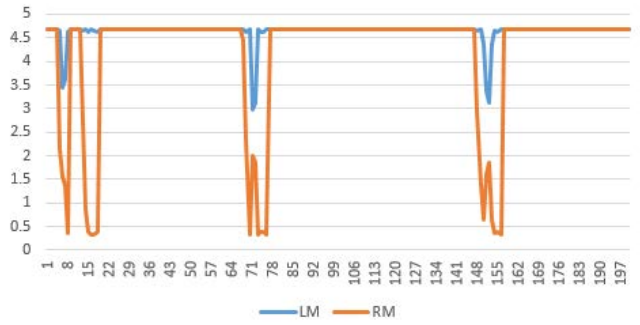

Fig. 17. Output values for Simulation 3

We can see that the velocities of each motor suddenly decreases as the robot encounters an obstacle, returning to the navigation at its maximal speed.

V. DESCRIPTION AND EXPLANATION

Due to the success of fuzzy logic application, researchers have implemented hybrid fuzzy techniques to bring learning capabilities to fuzzy logic systems. The most well-known approaches are Neuro-Fuzzy and Genetic-fuzzy systems.

Neuro-fuzzy or Fuzzy-neural networks is a hybrid fuzzy system that combines neural networks to learn the optimal parameters for a fuzzy system. These systems are classified in two categories: Adaptive Neuro-Fuzzy Inference Systems (ANFIS), where the neural network is trained with data from the surrounding environment to tune the fuzzy rules and fuzzy sets of the fuzzy inference system; and hybrid systems where the neural network and the fuzzy system work separately.

ANFIS, proposed by Roger in 1993[7], integrates fuzzy logic and neural networks in one framework. Due to performance it is highly used in mobile robotics, as in [8] an ANFIS with safe boundary algorithm improved the velocity of the robot and performance of navigation against curved and irregular obstacles. In [9] a comparison between ANFIS with different configuration was analysed, observing that trapezoidal function is the best performing function with more fuzzy sets for input target. Papers [19, 13] describes several techniques for navigation of mobile robot using ANFIS and hybrid fuzzy inference systems.

Biological-inspired techniques such as Genetic Algorithm, Particle Swarm Algorithm, Ant Colony Optimization, Firefly Algorithm, Artificial Immune System and Invasive Weed Optimization, to name a few, have been used in combination with Fuzzy Inference Systems to optimize the membership functions, generate an optimal rule base and for automatize the generation of rules and membership functions (knowledge base).

One of the most popular evolutionary computing used with fuzzy logic is Genetic Algorithm (GA). GA is a search algorithm inspired by evolutionary biology. The algorithm starts with a population of randomly generated individuals called chromosomes. This population undergoes evolution in a natural fashion and is evaluated through a fitness function, where the individuals are selected based on stochastic operators. After this process, a new population is generated, and the whole process is repeated until the termination condition is met.

Researchers have used GA stand alone, combined with neural networks for adding evolutionary learning to Fuzzy Inference Systems, and combined with fuzzy clustering algorithms for optimizing the parameters of Fuzzy C-Means systems (FCM).

Hybrid systems using Fuzzy logic and GA have been designed to control mobile robots in unknown environments, for optimizing path planning, improving smoothness in the movement, and avoiding obstacles. In [10] a hybrid Fuzzy Inference System using GA is used for path planning optimization for mobile robots under unknown environment with static and dynamic obstacles. In [11] a GA is implemented to generate an optimal path for a mobile robot which a fuzzy logic controller keeps track to drive the robot towards a target. In [12] a GA is used to tune the membership functions of a fuzzy logic controller for a mobile robot in an unknown environment with target tracking and obstacle avoidance behaviour. The results show that the combination of Fuzzy Logic with GA creates a smoother path, outperforming the FLC method in distance and time to reach the target.

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APPENDIX

Appendix 1: Fuzzy Rules

No.	FOD	ROD	LOD	LM	RM
1	Very_far			high	high
2	far	Not very_far	Not very_far	medium	medium
3	far	Very_far		high	low
4	far	Not very_far	Very_far	low	high
5	medium	Very_far		high	low
6	medium	Not very far	Very_far	low	high
7	medium	Not far	far	Low	high
8	medium	far	Not very_far	high	low
9	medium	medium	medium	low	low
10	medium	very_near	Not very_near	low	high
11	medium		Very_near	high	low
12	medium	near	near	high	low
13	near	Very_far		high	low
14	near	Not very_far	Very_far	low	high
15	near	Not far	far	low	high
16	near	far	Not very_far	high	low
17	near	medium	medium	high	low
18	near	near	near	high	low
19	near	very_near	Not very_near	low	high
20	near		Very_near	high	low
21	near	near	Not near	low	high
22	near	Not near	near	high	low
23	very_near	Very_far		high	low
24	very_near	Not very_far	Very_far	low	high
25	very_near	far	Not very_far	high	low
26	very_near	medium	medium	high	low
27	very_near	near	near	high	low
28	very_near	very_near	Not very_near	low	high
29	very_near		Very_near	high	Low
30	Very_near	Very_near	Very_near	high	low