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# Single Sensor Navigation for Unmanned Indoor Ground Vehicles Using Fuzzy Rules

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**Abstract: Obstacle detection and avoidance systems as a research area have been gaining attention lately, but the issues of blind areas and ground/small obstacle problems have received little interest, especially indoor autonomous navigation. In this work, we present an environment-sweep technique for obstacle detection and a fuzzy algorithm for ground obstacle avoidance, surface elevation estimation, and obstacle classification for indoor robots that eliminates the blind area problem. We employed an ultrasonic sensor on a servo for environmental sweep to eliminate blind areas. Results show that the issue of interference was mitigated by the servo sweep technique we propose. Fuzzy algorithms combined with a single ultrasonic sensor reduced the complexity of the robot, thereby improving the robot's performance in real-time. Fuzzy algorithms combined with a differential wheel driving mechanism speed up the inference and actuation process of the proposed system. This is due to fewer rules and a less complex yet effective algorithm design that converts steering angles to different wheel speeds, making the response time much less than the stipulated threshold of 2s as has been determined in previous literature.**

***Keywords:*** *Self-Adaptation, Linear Regression, Environmental Variant, Design Pattern, Reusability, Software Variant, Load Balancer.*

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## I. INTRODUCTION

Intelligent Transportation Systems (ITS), as referenced in [1], have a clear mission: to replace human-driven decisions and actions with systematic, precise machine assistance. The result of this endeavor is the emergence of Advanced Driver-Assistance Systems (ADAS) [2, 3, 4, 5]. ADAS systems are designed to enhance driving processes, offering features like pothole alerts, road lane detection, adaptive cruise control, and parking assistance. These systems have made significant strides in reducing road accidents [6] and enhancing traffic flow. Yet, their full potential remains untapped in challenging environments such as conflict zones or disaster areas. This underscores the need for fully automated driving systems, including autonomous ground vehicles and unmanned aerial vehicles.

Autonomous ground vehicles, also known as Unmanned Ground Vehicles (UGVs), represent a fascinating branch of intelligent vehicular robotics. These vehicles rely on algorithms to make driving decisions, including steering, speed control, and braking, thereby simulating human intelligence and actions. They navigate through their environments—be it indoor, outdoor, or off-road—where obstacles are the rule rather than the exception. As such, autonomous vehicles must incorporate robust sensing systems for obstacle detection and collision avoidance mechanisms. While some rely on pre-stored world maps for obstacle-free path planning, this approach restricts their operational scope to predefined environments.

In parallel with obstacle-detection sensors, collision avoidance mechanisms are integral to the autonomous vehicle's functionality. These mechanisms halt the vehicle when an obstacle is detected or employ control strategies to navigate around the obstruction. Controllers, which may be Proportional, Integral, and Differential (PID) or Adaptive controllers, play a crucial role in implementing these avoidance decisions.

A primary challenge in implementing autonomous vehicles lies in obstacle detection and collision avoidance. Initially, Global Positioning System (GPS) technology was used to provide environmental information to these vehicles [7]. However, relying solely on GPS can be problematic, as not all areas are covered, and GPS signals can be prone to interference, rendering it unsuitable for indoor environments. An alternative approach involves utilizing a pre-defined world map for obstacle-free path planning, with the vehicle acting as a target-based agent [8, 9, 10]. However, this method is susceptible to issues like local trapping and oscillatory wandering when confronted with multiple or sizable obstacles [11, 12].

Recent advancements have shifted towards sensor-based approaches, where autonomous vehicles rely predominantly on sensor information for obstacle detection. Stereo cameras were initially employed for this purpose but incurred high computational costs, despite providing extensive environmental information. Hybrid methods exist, combining world models/maps with sensor data for obstacle detection and path-planning [13]. However, this approach demands complex algorithms to select optimal paths to the target, introducing computational overhead.

Sonar sensors, including ultrasonic and infrared sensors, have emerged as superior options for indoor environment sensing. They operate with low energy consumption, minimal computational demands, and are insensitive to ambient light conditions. Similarly, collision avoidance can be implemented through various methods. [4] Categorized these methods into model-based and reactive-based approaches. Model-based methods involve conventional controllers such as proportional and integral (PI) or proportional, integral, and differential (PID) controllers for collision avoidance. While they offer precision, they are limited to basic forward-backward and left-right movements and can suffer computational overhead, particularly during curved path simulations.

In contrast, reactive-based methods, like fuzzy logic and neural networks, have proven effective for collision avoidance due to their speed and ease of implementation. Fuzzy controllers, for instance, can adjust steering angles and speeds, facilitating the generation of curved paths around obstacles without coming to a halt.

The effectiveness of any obstacle detection and avoidance system hinges on its real-time performance [14]. Fuzzy logic, known for its rapid implementation and smooth control [15], presents an ideal candidate for real-time, time-dependent robot motion implementation.

Hence, our proposal centers on a sonar-based sensing approach and a fuzzy logic reactive-based strategy to create an obstacle detection and avoidance system for autonomous vehicles. This approach streamlines the system by employing a single ultrasonic sensor mounted on a servo motor for a broader environmental sweep. By merging sonar technology and fuzzy logic, we aim to achieve swiftness, as the system processes fewer fuzzy rules, expediting the search for the appropriate rule to execute.

In summary, this work addresses the critical challenges of obstacle detection and collision avoidance in autonomous vehicles, offering a novel approach that combines sonar-based sensing with efficient fuzzy logic control to enhance real-time obstacle navigation.

Indoor environments, such as factories, warehouses, and residential spaces, present distinct challenges compared to conventional highways. They are characterized by limited space, unstructured pathways, and a lack of predefined road signs or markings, making them inherently dynamic and prone to uncertainties. Navigating through such indoor spaces demands heightened adaptability and responsiveness from autonomous systems.

Numerous approaches have been proposed to address the complexities of indoor autonomous navigation. Some efforts, like those documented in [16, 17, 18, 19], have focused on detecting sizable objects elevated above ground level. While these endeavors have contributed valuable insights, they fall short in addressing certain critical issues. Notably, prior work, exemplified by [20, 21, 22], has demonstrated success in detecting obstacles of varying sizes, including their heights. However, these achievements have not been without their challenges.

One persistent issue is the presence of disruptive "salt and pepper" noise in camera images; a complication vividly illustrated in the case of [20]. Additionally, the utilization of multiple ultrasonic sensors to mitigate blind spots, as observed in [21], introduces the problem of interference. Furthermore, computational overhead has hindered real-time system performance when processing frequency-modulated continuous waves, as highlighted in previous research [22]. Moreover, the spatial model employed thus far is ill-suited for accurately estimating the fuzzy heights of obstacles.

To address these limitations and provide a comprehensive solution, there is a pressing need for a robust system capable of detecting obstacles across a wider range while eliminating the challenges associated with blind spots. Such a system should not only exhibit low computational and operational costs but also integrate seamlessly with a reactive-based collision avoidance mechanism. This holistic approach aims not only to enhance system performance but also to significantly reduce the risk of failures during autonomous navigation.

Therefore, we propose a novel solution that combines a single ultrasonic sensor, strategically mounted on a servo motor, for obstacle detection. Complementing this sensor setup is the implementation of a fuzzy logic algorithm within the autonomous controller. Our work is motivated by the overarching goal of designing and deploying a real-time obstacle detection and avoidance system for autonomous vehicles. This system is engineered to deliver high reactivity while maintaining low computational costs, ultimately contributing to safer and more efficient autonomous navigation in indoor environments.

This paper follows a structured organization. Section 2, "Review of Related Works," we provide an overview of existing indoor autonomous navigation approaches, with a focus on their limitations. Section 3, "Methodology," delves into how our research endeavors to overcome these identified limitations. The tools, materials, and architecture of the proposed system are detailed in this Section as "System Development. Section 4, "Implementation and Testing," presents the outcomes of both real-world and simulation tests. Section 5, "Discussion," scrutinizes our findings and elucidates their implications for indoor autonomous navigation; Finally, Section 6, "Comparative Analysis with Existing Works," offers a comparative assessment of our

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methodology when juxtaposed with similar approaches and Section Concludes the work.

## II. LITERATURE REVIEW

The realm of obstacle detection and avoidance systems has been extensively explored within both indoor and outdoor environments, with various approaches employing optical flow, sonar, and other technologies. Among the early outdoor works, [23] stands out as a pioneer, introducing the concept of perception control for cross-country rovers. This system hinged on a stereo imaging setup to detect obstacles through pixel-level height comparisons. However, its reliance on a cropped window of attention (CWA) limited its detection range and subsequently slowed down rover speed. Moreover, the computational demands associated with pixel-to-pixel comparisons remained a challenge.

In a similar vein, [24] introduced a real-time stereo image processing technique for autonomous off-road navigation. This method, based on horizontal concepts, evaluated the vertical flatness of the rover track. While it eliminated the need for pixel-to-pixel comparisons, it introduced complexities related to establishing a stable ground plane. Furthermore, issues arose when the camera lost alignment with the ground plane due to rover tilt and roll, leading to false alarms.

Efforts to overcome these limitations led to [7], which presented a novel obstacle detection and terrain classification approach for autonomous off-road navigation. This algorithm identified compatible points within a projected triangular sector on the image point cloud, effectively speeding up obstacle detection by accommodating varying window sizes. Nevertheless, challenges persisted in parameter selection, particularly in setting maximum and minimum height thresholds.

Shifting focus to laser-based techniques, [25] introduced first-order statistical models for discrete obstacle detection in 2D laser image maps. By employing discrete integral and standard deviation calculations, this approach accurately estimates obstacle height, even for objects as small as 20cm at a distance of 60m. However, practical implementation relied on road reflectance parameters for calibrating reference images, limiting its applicability due to variations in road surfaces.

Transitioning to indoor settings, we encounter challenges like image noise, exemplified in [26]. This work aimed to create a robust height measurement system for intelligent home service robots using a stereo camera. Despite its rapid obstacle detection through neural network-based surface training, challenges arose in height error measurement due to light variations and perspective factors.

Recognizing the noise issues inherent to indoor environments, [27] proposed obstacle avoidance with ultrasonic sensors for navigating indoors. The system featured a pair of sonar sensors on a mobile robot, offering cost-effectiveness and resilience to light variability. However, uncertainties in obstacle distance measurement and inaccuracies in object location persisted due to sensor angular depression.

In the context of auto parking systems, [21] introduced an ultrasonic array-based obstacle detection approach using multiple sensors at the rear of a Sport Utility Vehicle (SUV). This method addressed the parallax error and blind spot problems by segmenting distance ranges into safe, middle, and warning areas. However, susceptibility to interference among echo signals posed a challenge.

Taking a different route, [22] proposed Doppler shift and height detection of obstacles via a frequency-modulated continuous wave (FMCW) sensor. This radar-based system showed promise in mitigating interference and blind spots, with simulation results indicating improved height estimation compared to [21]. Nevertheless, the spatial model employed struggled to capture the irregular and fuzzy nature of obstacle heights.

More recently, [28] introduced a low-cost ultrasonic distance sensor for obstacle avoidance in mobile robot navigation, demonstrating effectiveness across various lighting conditions. Additionally, a novel approach involving road sign detection was explored in [29], incorporating visual information and Cascade Classifier training for road sign recognition.

Building upon the insights from these works, our approach enhances [22] and improves [21] by utilizing a sonar sensor mounted on a servo for broader environmental coverage. Furthermore, we incorporate a fuzzy algorithm to estimate obstacle heights, acknowledging the inherent fuzziness in height transitions from safe to traversable to dangerous. This comprehensive system will leverage fuzzy algorithms for dynamic control, curved path simulation, and speed regulation during collision avoidance maneuvers.

- *Limitations of Existing Works*

Interference Vulnerability: Prior methodologies, such as the ultrasonic array-based approach [21], are prone to interference issues among sensor signals. This limitation affects the accuracy of obstacle detection and can lead to false alarms.

Height Estimation Challenges: Some approaches, like the FMCW radar-based system [22], encounter difficulties when estimating obstacle height, particularly when dealing with irregularly shaped objects. This limitation may result in inaccurate height assessments.

Distance-Related Accuracy: The use of stereo cameras [20] for obstacle detection may suffer from increasing height measurement errors as the distance from the obstacle grows due to image noise. This limitation impacts the system's accuracy at longer distances.

- *Addressing Limitations in Our Proposed Work*

Interference Mitigation: Our proposed system employs a servo sweep concept that addresses interference issues

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effectively. By covering a wide viewing angle, our approach minimizes interference among sonar signals. The servo sweep enhances adaptability and reduces the vulnerability to false alarms, as demonstrated in our real-world tests and simulations (Figures 13, 14, 15, 17 and 18).

Comprehensive Height Classification: In contrast to prior works, our fuzzy algorithm accommodates the full range of potential obstacle heights, including irregular shapes. This comprehensive height classification ensures precise and reliable height categorization (Figure 8). The min-max defuzzification method resolves any conflicts when an obstacle height corresponds to multiple membership functions.

Distance-Aware Response: Our system exhibits a faster response time, as validated in both real-world tests and simulations. The response time comfortably falls within the 2-second threshold proposed by [30], indicating that our system effectively addresses emergency situations and responds promptly to obstacles at close range.

By systematically addressing these limitations of existing works, our proposed system offers a more robust and adaptive solution for indoor autonomous robot obstacle detection and avoidance. It mitigates interference, enhances height classification accuracy, and ensures a rapid response, thereby contributing to safer and more reliable indoor robot navigation.

## III. METHODOLOGY

In this study, we aim to design, simulate, and implement a functional rover prototype for testing our obstacle detection and avoidance algorithms. Our recourse to prototyping hinges on the fact that some algorithmic simulation software may not capture all the characteristics of the real-world environment. Moreover, in recent years we have witnessed a flood of small robots and mechatronic devices that are suitable for testing algorithms. These devices, though small and cheap, are fashioned with capabilities to test very complex systems. Examples of such devices are the iRobot [31], CareBot [32], Arduino rover [33, 34], and their variants. Our implementation began with the simulation of the controller in MATLAB which was tested in VREP after which the prototype rover was constructed. The system was programmed with Arduino, a C-style programming language, and the controller was developed with the help of the embedded fuzzy logic library (eFLL). The fuzzy controller contains the if-then rules for the system's decision-making. These represent the system's reaction on pinging an obstacle modeled with fuzzy if-then rules and stored in the fuzzy rules base. The inputs to the fuzzy controller are the position, distance, and height of the obstacle from the rover. These inputs were represented using trapezoidal membership functions to yield a corresponding steering angle which in turn are converted to left and right wheel speeds.

### *A. Tools and Materials*

The devices used for the implementation of the rover prototype are:

- Arduino Uno Microcontroller.
- An ultrasonic sensor that senses the environment and communicates to the system the presence of obstacles.
- Power: one 9V battery and four 1.5V batteries supply the system with electric power.
- A Caster Arduino robot kit containing: a pair of DC motors, an LMP motor driver, a 5V sensor shield, a servo, etc.
- One HC-06 Bluetooth module

➢ *Software and Programming Language*

Coding was carried out before and during the simulation and prototyping phases. After the controller was designed in MATLAB, it was deployed to control a virtual robot in VREP using Python. Performance results from sensors and outputs from the controller were transmitted to a PC via Bluetooth and Teraterm software. Below is the list of all software tools and programming languages used for the implementation of the system.

- MATLAB – R2015a
- Arduino IDE version 1.6.8
- VREP version
- Spyder2
- TeraTerm version 4.9.6
- C/C++ programming language
- Extended fuzzy logic library
- Python 2.7

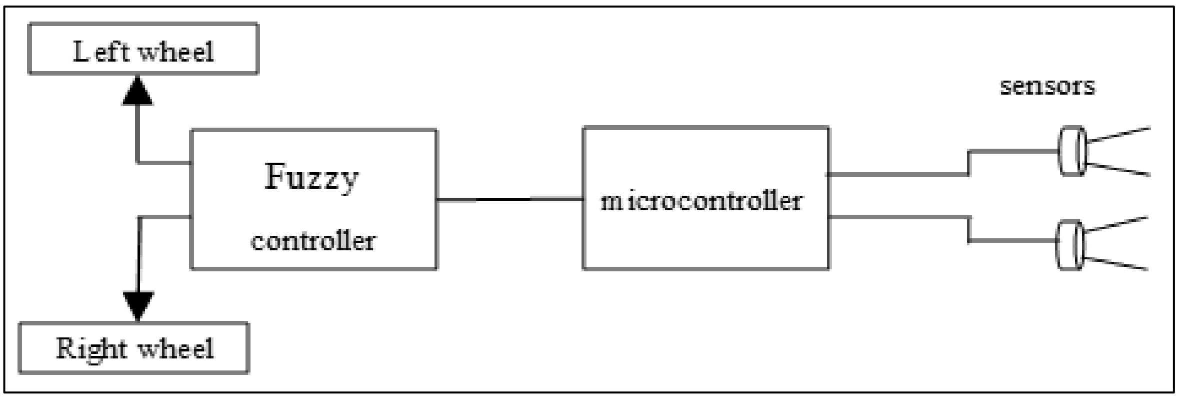


Fig 1 Architecture of the Proposed System.

- *Architecture of the Proposed System*

Figure 1 depicts the architecture of the proposed autonomous vehicle. At the front is a sensor with which the system continuously senses the environment. The ultrasonic transmitter transmits sound waves and receives an echo whenever an obstacle reflects the waves signifying a hit in the obstacle detection process. The distance and angle are passed to the fuzzy controller for processing. The fuzzy controller then decides whether or not to make a detour. Whatever the system resolves, the fuzzy controller assigns appropriate speeds to the wheels for navigation. In the case where a detour is guaranteed, the fuzzy controller's steering angle is converted to different speeds to the wheels, consequently allowing for a change in direction.

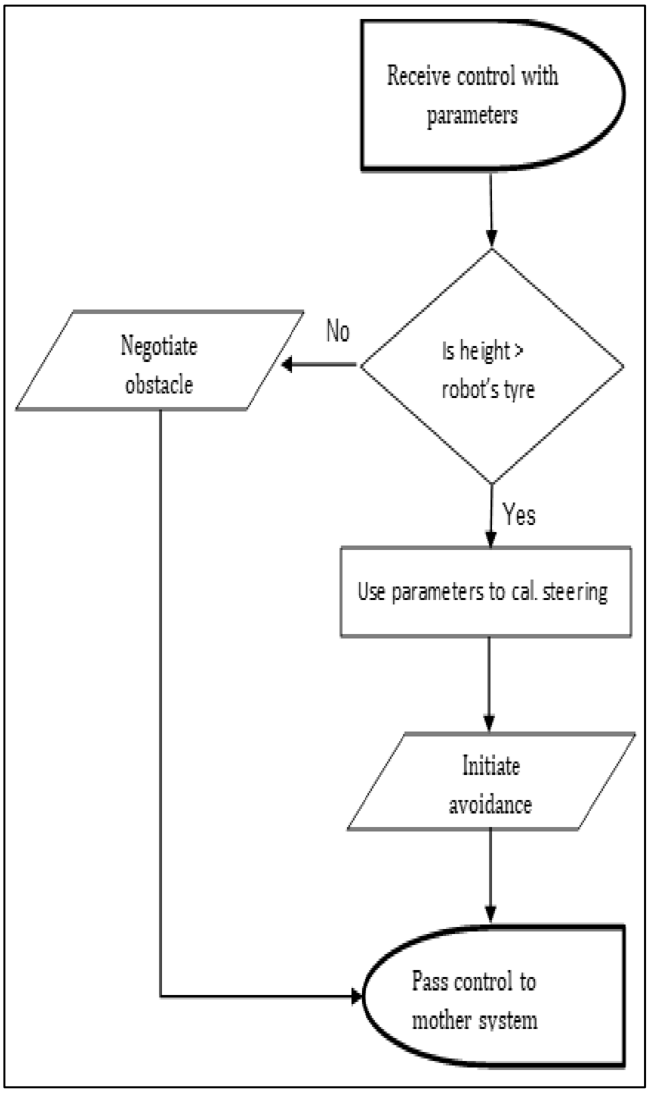


Fig 2 Flowchart of the General Operation of the ODAS.

Figure 2 shows the flow chart for the proposed system. The flow begins with an initialization of the system. The robot then continues to move at average speed. Once an obstacle is sensed, the system receives input parameters and responds as appropriate. The distance is used to ascertain the obstacle's height and the controller assigns the necessary speeds to negotiate it. If there is no obstacle, the robot continues at average speed.

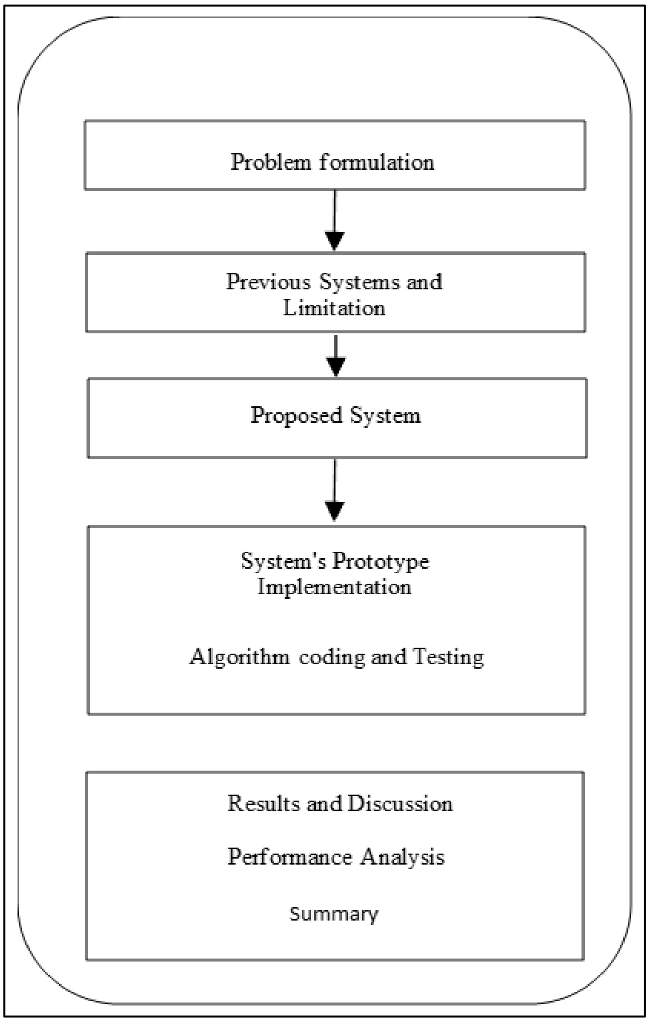


Fig 3 Framework of the Proposed System.

Here is a diagrammatic representation of the work plan of the proposed system. The framework presents a hierarchical sequence of activities involved in the implementation of the proposed system.

*B. Implementation and Testing*

The proposed obstacle detection and avoidance system (ODAS) implementation conform to the Mamdani fuzzy system which transforms input variables (from sensors) to output variables (for actuators) using fuzzy rules. Trapezoidal membership functions were used to represent variables, and a min-max defuzzification method was employed to process results from the fired fuzzy rules in both the simulated environment and the prototype. Results (discrete sensor readings) from the simulation in MATLAB's fuzzy logic toolbox were compared to that of the prototype in a real-world scenario.

- *Fuzzy Controller Design*

Fuzzy logic systems closely replicate human expertise. This is also true for autonomous systems. This expertise is represented as fuzzy if-then rules in the fuzzy controller and our case; the expertise is driving. Hence, inputs like obstacle distance and position are obtained from the environment and fed to the controller. The controller then gives out steering angles which are subsequently converted to differential

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speeds for the actuators, i.e., the road wheels. The following sections contain various aspects of the fuzzy controller implementation.

➢ *System Variables*

The following are the input and output variables that represent the membership functions of the proposed fuzzy controller. The inputs to the system are:

- Obstacle position (φ) to servo angle
- Obstacle distance (D)
- Surface elevation/ground object height (H)

The outputs from the controller after processing the inputs are:

- Speed (S)
- Steering angle (θ)

➢ *Variables Range and Sensor/Servo Calibration*

The variables for the fuzzy controller are well ranged, i.e., they are associated with intervals of values that an input or output may assume. For example, at any distance between 2cm to 50cm, any object pinged within this range is termed an obstacle. The servo position (in degrees) on which the obstacle was pinged represents the obstacle angle. Below are all the ranges for the system variables.

- Distance (i.e., Ultrasonic sensor's far and near point) = [2cm−50cm]
- Obstacle position (servo angle) = [300 −1200]
- Surface elevation/ground object height (in voltage level) = [0,4]
- Robot speed range = [80rev/s − 105rev/s]
- Steering angle range = [−200 to +1200)]

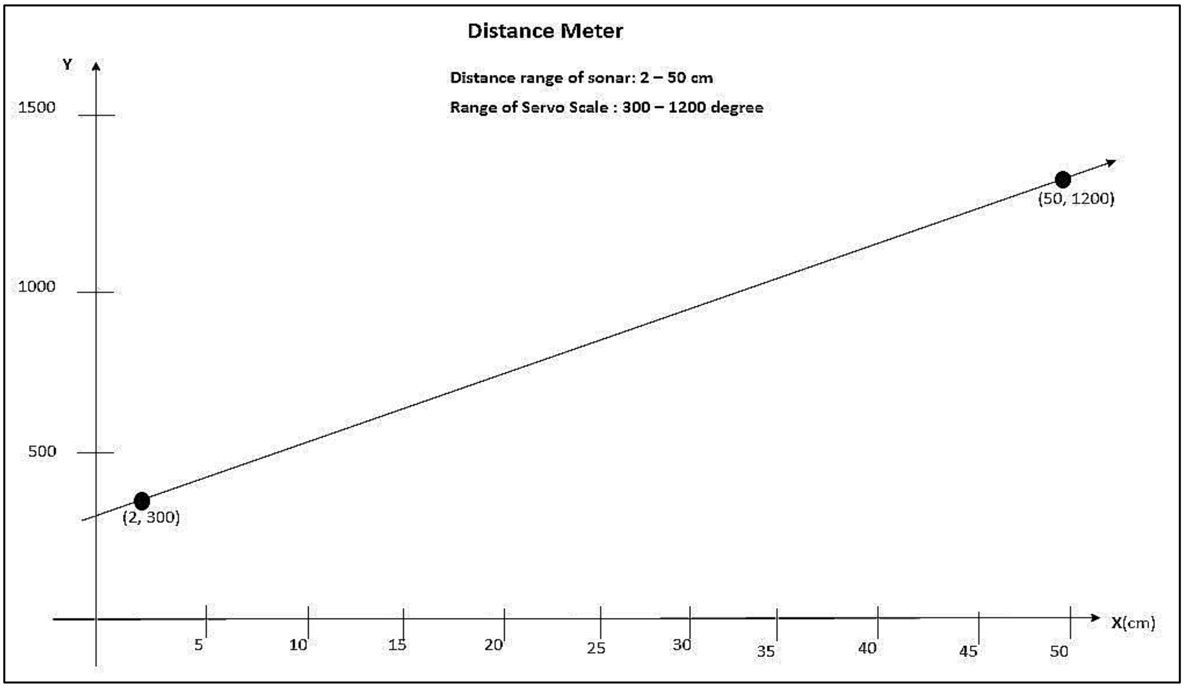


Fig 4 Distance Meter Model for the System.

The X-axis represents the possible measurable distance of a sonar sensor shown in Figure 4 with the x-axis representing the servo angles. Thus:

$$\text{Slope} = \frac{y_2 - y_1}{x_2 - x_1} = \frac{1200-300}{50-2} = \frac{900}{48} \tag{1}$$

$$y_2 - y_1 = \text{m}(x - x_1)(y - 300) = \frac{900}{48}(x - 300) \tag{2}$$

$$y = \left(\frac{900}{48}\right)(x - 2) + 300$$

$$Servo\ Angle = \left(\frac{900}{48}\right)(x - 2) + 300 \tag{3}$$

➢ *Delimiting the Fuzzy Set Variables*

Every variable consists of some sets that categorize all possible values for the inputs/outputs for that variable. These sets are represented with acronyms for easy usage as they form the antecedents and consequents of the fuzzy if-then rules in the rules base.

- Distance: [Far (FR), Safe (SF), Close (CL)]
- Obstacle position: [Lefter (LT), Left (L), Straight (S), Right (R), Righter (RT)]
- Surface elevation: [flat (FLT), high (HIG), higher (HGR)]
- Speed: [Fast (FST), Average (AVG), Slow (SLW)]
- Steering angle: [Negative big (NB) Negative small (NS), Zero (Z), Positive small (PS), Positive Big (PB)]

Once these variables are partitioned into sets, the next step is to associate each set with some numerical value. MATLAB was used to auto-generate the membership functions which consist of these sets as seen in Figure 5.

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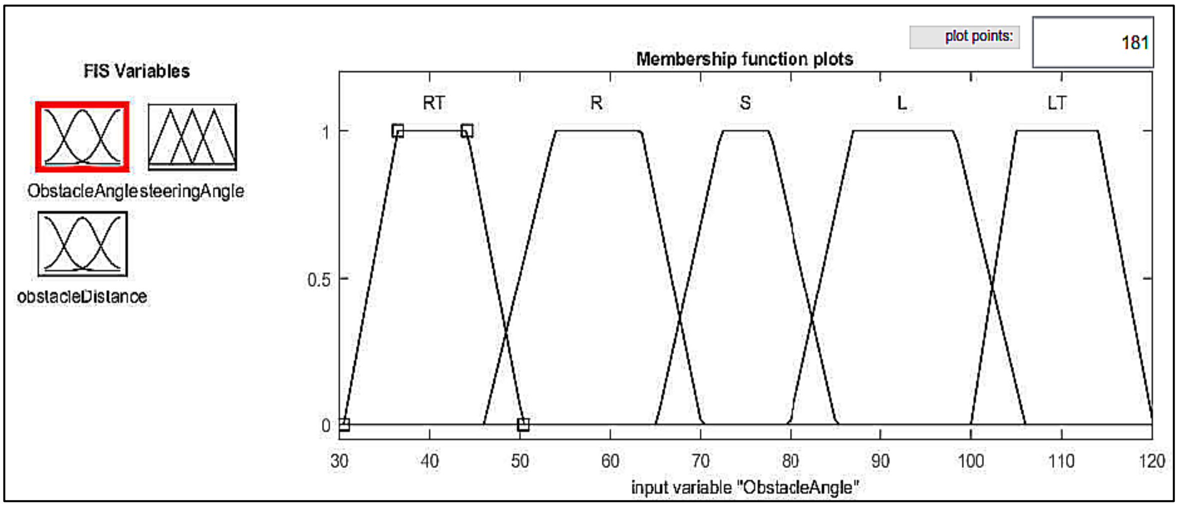


Fig 5 Membership Function for Obstacle Position.

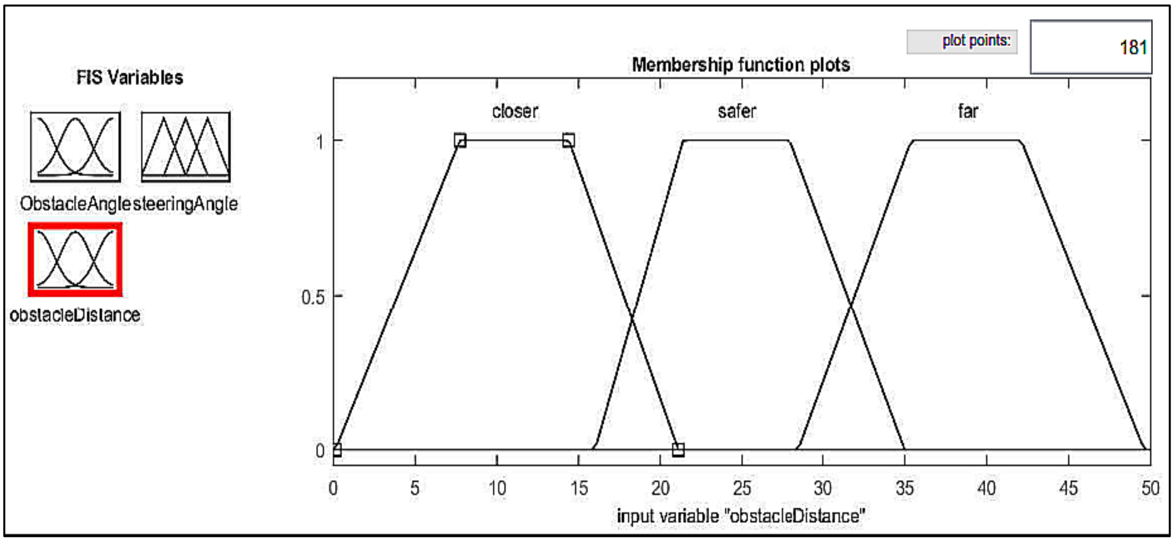


Fig 6 Membership Function for Obstacle Distance.

Once these variables are partitioned into sets, the next step is to associate each set with some numerical value. MATLAB was used to auto-generate the membership functions which consist of these sets as seen in Figure 1.

➤ *Fuzzy Rule for Big Obstacle*

Table 1 is the summary of the if-then rules that represent the rule base for the autonomous controller.

Table 1 Symbolic Representation of the Antecedents and Consequents for the Fuzzy Rules

| **Distance/position** | **Lefter (LT)** | **Left (L)** | **Straight (S)** | **Right (R)** | **Righter (R)** |
|---|---|---|---|---|---|
| Closer (**CL**) | Positive Big (**PB**) | Positive Small (**PS**) | Negative Big (**NB**) | Negative Big (**NB**) | Negative Small (**NS**) |
| Safer (**SF**) | Positive Small (**PS**) | Positive Small (**PS**) | Positive small (**PS**) | Negative Big (**NB**) | Negative Small (**NS**) |
| Far (**FR**) | Zero (**Z**) | Zero (**Z**) | Zero (**Z**) | Zero (**Z**) | Zero (**Z**) |

➤ *Steering Angle*

The heading represents the obstacle’s position of membership function while the leftmost column is the distance variable or membership function. The body of the table captures the steering angle, which is the result of the heading and the leftmost column. For example, applying the first CL (closer) and LT (lefter) results in PB (positive big). When every leftmost column (i.e., distance) is applied to all the heading rows (i.e., position), the following rules were obtained.

- If (obstacleAngle is RT) and(obsacleDistance is closer) then (steeringAngle is NS)
- If (obstacleAngle is R) and (obsacleDistance is closer) then (steeringAngle is NB)
- If (obstacleAngle is S) and (obsacleDistance is closer) then (steeringAngle is NB) If (obstacleAngle is L) and obsacleDistance is closer) then (steeringAngle is PB)
- If (obstacleAngle is LT) and obsacleDistance is closer) then (steeringAngle is PS)

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- If (obstacleAngle is RT) an (obsacleDistance is safer) then (steeringAngle is NS) If (obstacleAngle is R) and (obsacleDistance is safer) then (steeringAngle is NS)
- If (obstacleAngle is L) and (obsacleDistance is safer) then (steeringAngle is PS)
- If (obstacleAngle is LT) and (obsacleDistance is safer) then (steeringAngle is PS)
- If (obstacleAngle is S) and (obsacleDistance is safer) then (steeringAngle is PS) If (obstacleAngle is RT) and (obsacleDistance is far) then (steeringAngle is Z)

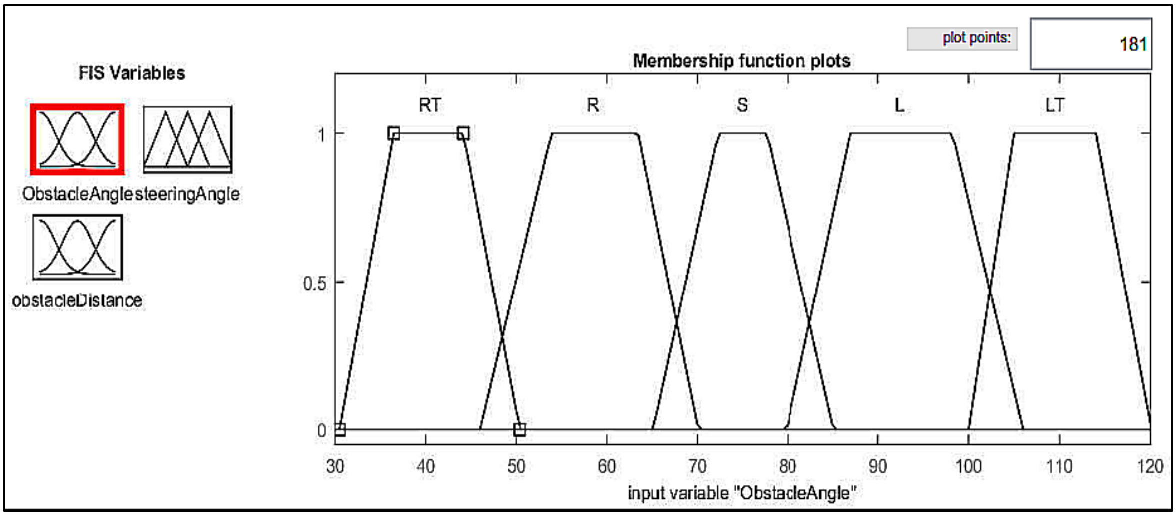


Fig 7 Membership Function for Steering Angle.

➢ *Fuzzy Rule for Small Obstacle/Surface Elevation*

The following rules were obtained for small obstacle negotiation control.

- If (surfaceElevation is flat) then (RobotSpeed is slow)
- If (surfaceElevation is high) then (RobotSpeed is average)
- If (surfaceElevation is higher) then (RobotSpeed is fast)

➢ *Simulation of the ODAS Controller*

MATLAB comes with a fuzzy logic toolbox that simplifies the design and simulation of a fuzzy system. It presents an easy-to-use graphical user interface for the design and simulation process. It also generates a MATLAB code for the full Simulink system simulation. Figure 7 represents the membership function for the steering angle; the left-hand side denotes the inputs (i.e., obstacle distance and angle), and the right-hand side represents the output (steering angle). Between the inputs and the output is the rules base. This shows the flow of the whole controller. That is, fuzzified inputs are passed to the controller which fires a rule that serves these inputs after which the output is defuzzified with the min-max defuzzification method. Figure 4 is a basic configuration of a fuzzy logic system.

*C. Prototyping the Autonomous Robot*

Before the proposed system coding, the system algorithm was developed in MATLAB. Python's SciKit was used for the controller simulation in V-REP. On the Arduino platform, eFFL was used in the coding of the fuzzy controller. Dependencies which are zero-or-one-of-group, exactly-one-of-group, at-least-one-of-group, zero-or-all-of-group, and parent-child relations. These are defined as follows.

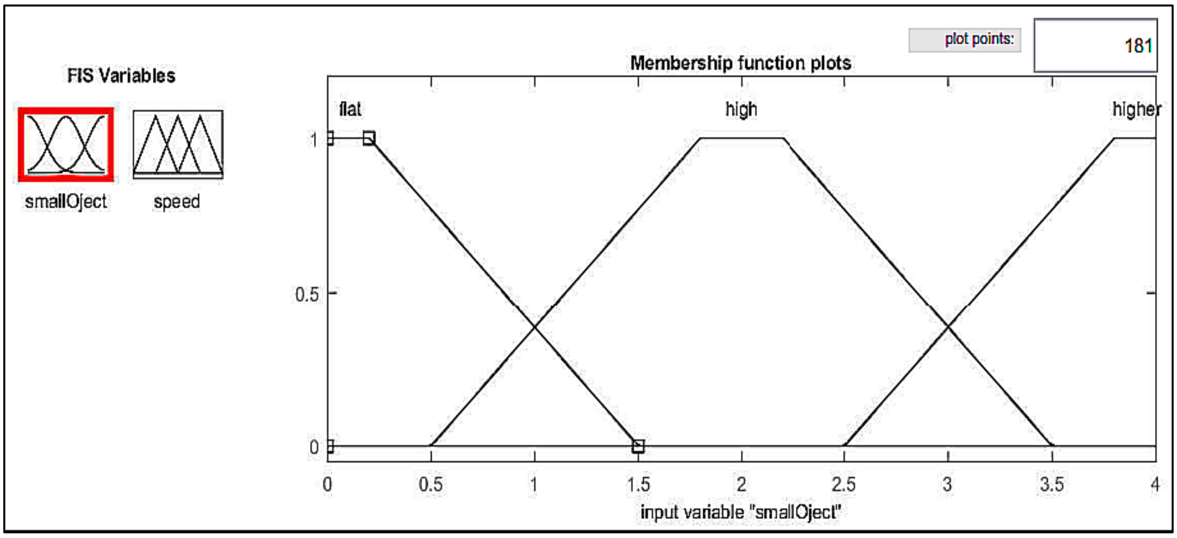


Fig 8 Input Variable for Small Obstacle Height

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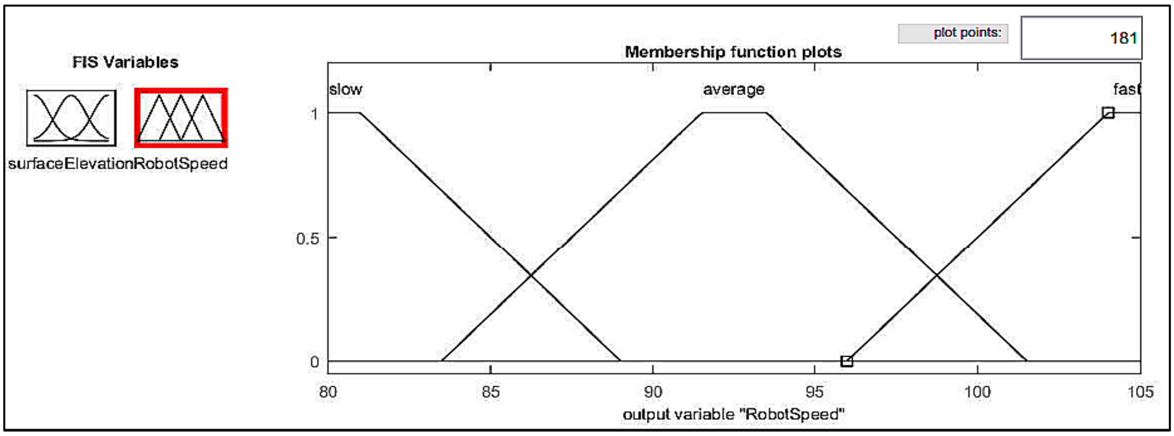


Fig 9 Output Variable for Small Obstacle

## IV. RESULTS AND DISCUSSION

This section presents results from MATLAB, VREP, and robot prototypes. MATLAB's results for the controller simulation show the robot's behavior as defined by the rules in the rule base. The VREP results are more of the practical application of the controller in a virtual environment. The real-world results are presented as a validation of the results in MATLAB.

### *A. Simulation Results*

Figure 11 is a three-dimensional MATLAB simulation graph of the 'big' obstacle detection and avoidance controller. The x and z coordinates represent the obstacle's distance and angle respectively, with the y coordinate indicating the steering angle. Using the min-max defuzzification method, the graph illustrates the outcomes for all possible inputs.

Figures 14 and 15 are results from the MATLAB controller simulation. They capture the entire behaviour of the robot as defined by the rules in the rules base of the controller. The results show that, at a distance of 0 through 50cm and at a position 200 through 1200, an obstacle can be detected and avoided within these ranges. Figure 8 shows the relationship between the obstacle's height/surface elevation and the robot's speed. The fuzziness of the obstacle height has been fully captured, and the robot behavior recognizes this.

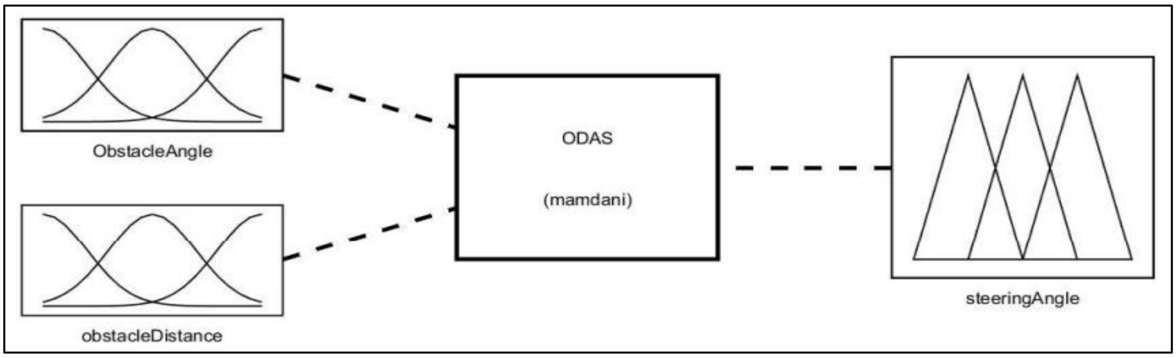


Fig 10 Fuzzy Controller Simulation in MATLAB

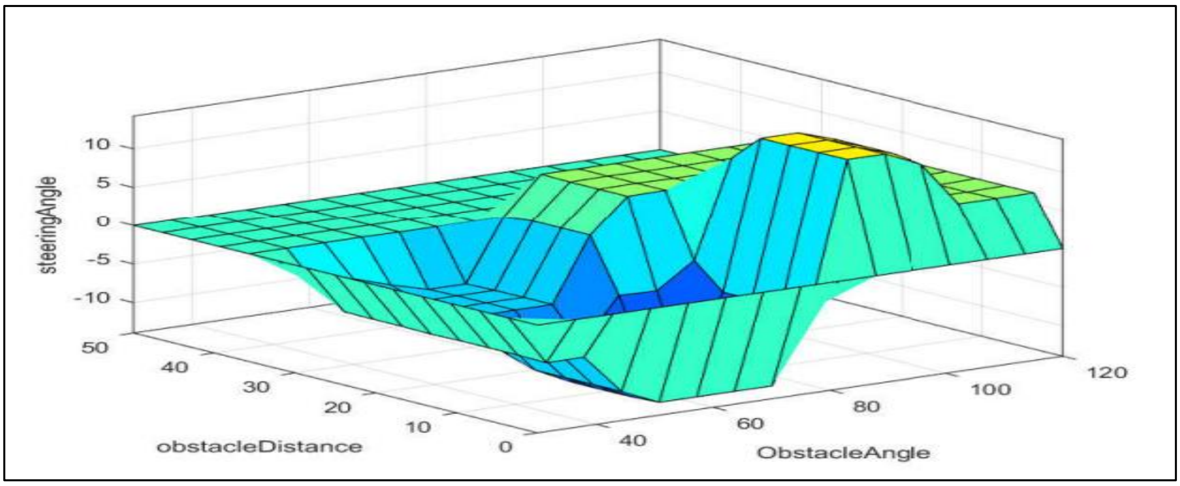


Fig 11 MATLAB Surface View of the Big Obstacle Detection Controller

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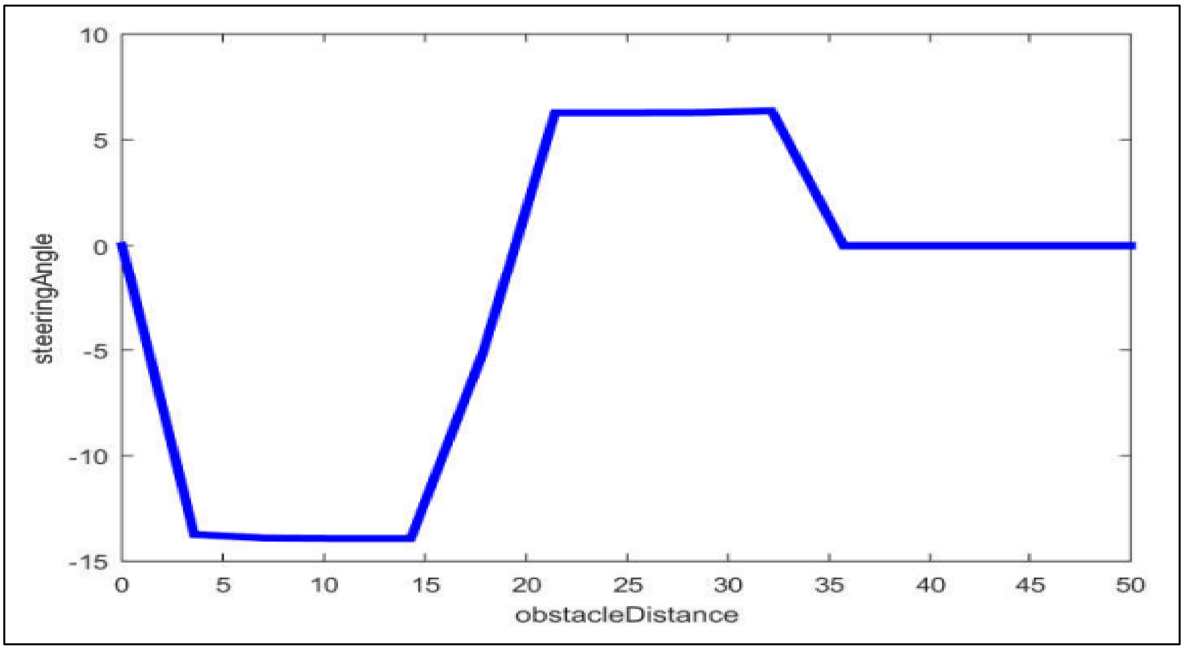


Fig 12 MATLAB Surface View of Steering Angle vs Obstacle Distance


Fig 13 (a, b, c): Results from the Real-World Test

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### *B. Prototype Performance Results*

The second method employed to test the proposed system is the prototyping of the system. Figure 13 present results obtained from the real-world test. Readings from the ultrasonic sensor covered all the angle ranges.

This shows that the concept of using servo sweep that mitigates the blind area problem without having to contend with interference. Figures 16, 17, and 18 represent a validation of our approach.

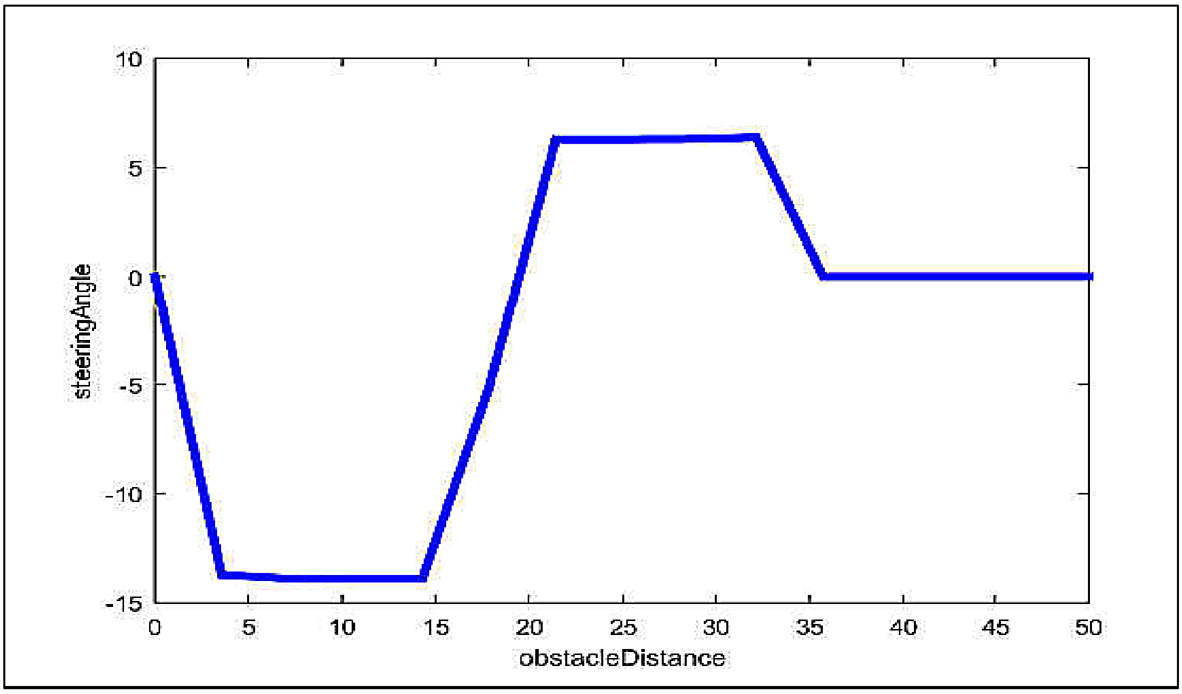


Fig 14 Surface View of Steering Angle vs Obstacle Angle

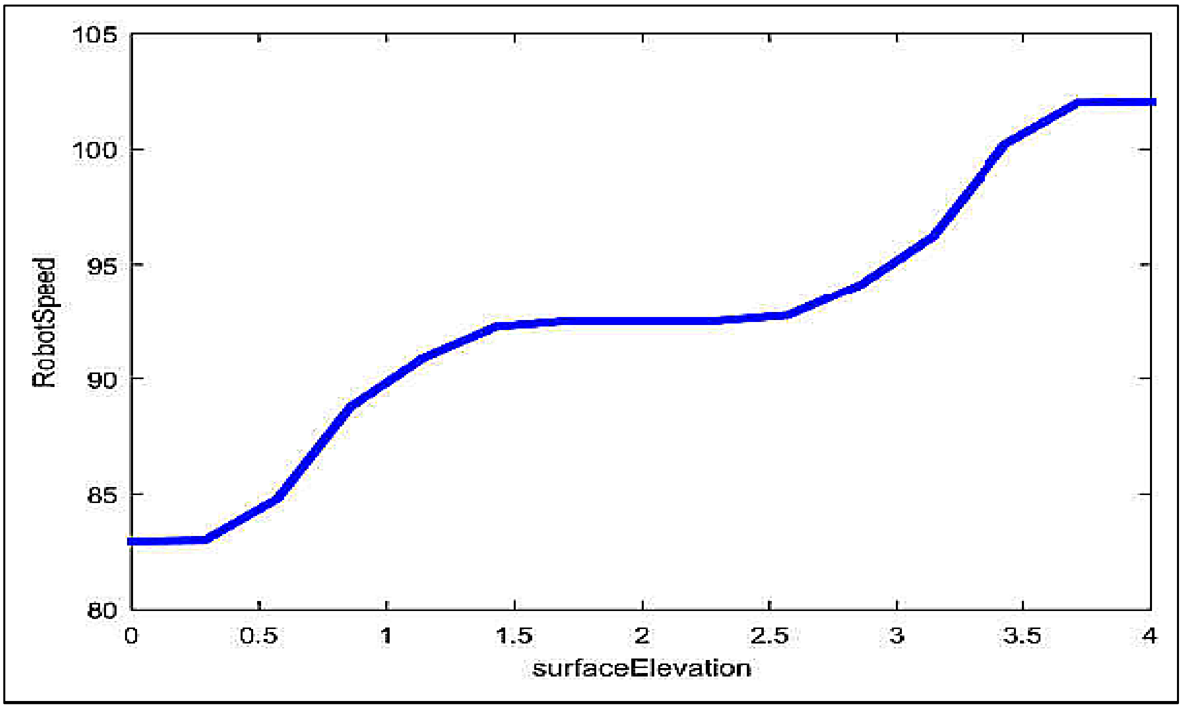


Fig 15 Small Object Surface View of Steering Angle vs Obstacle Distance

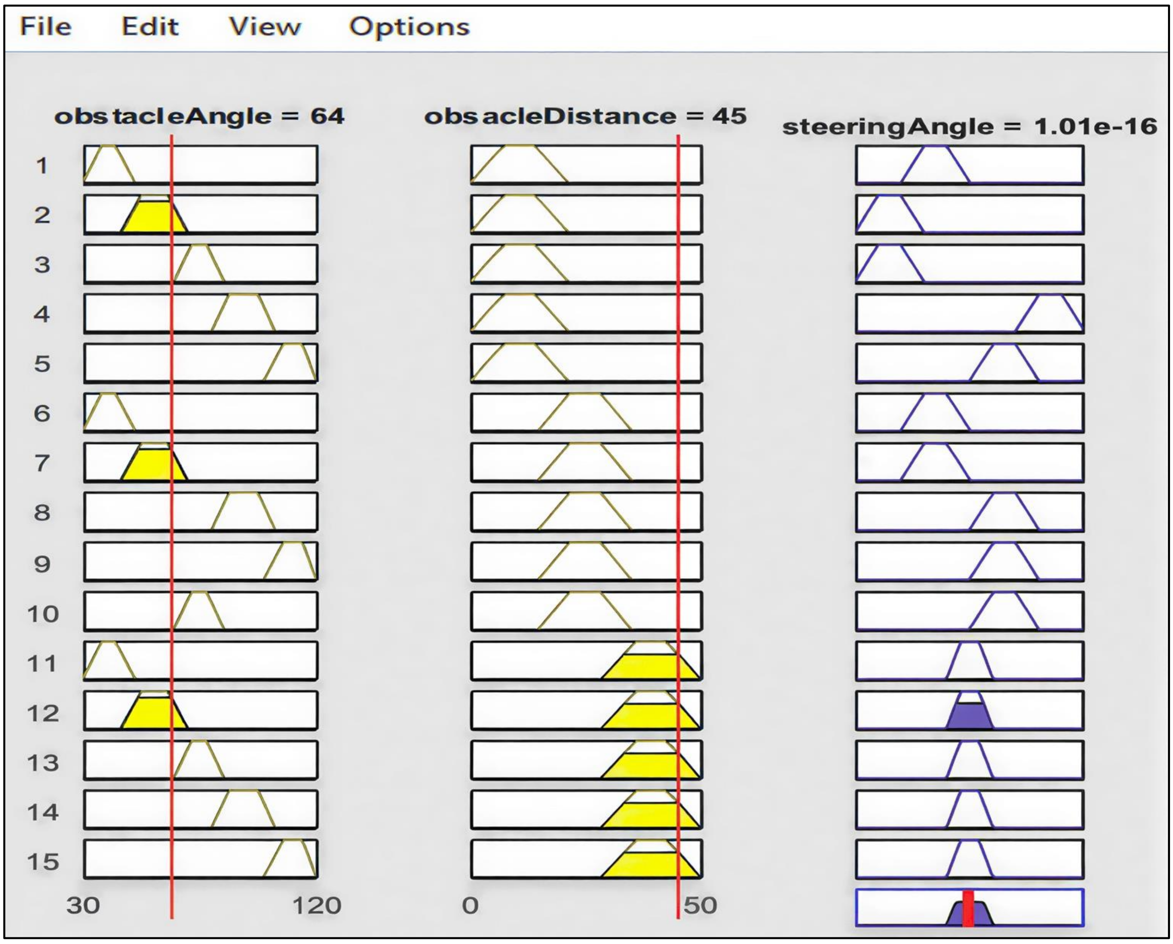


Fig 16 MATLAB Simulation Rule Viewer for the ODAS (a)

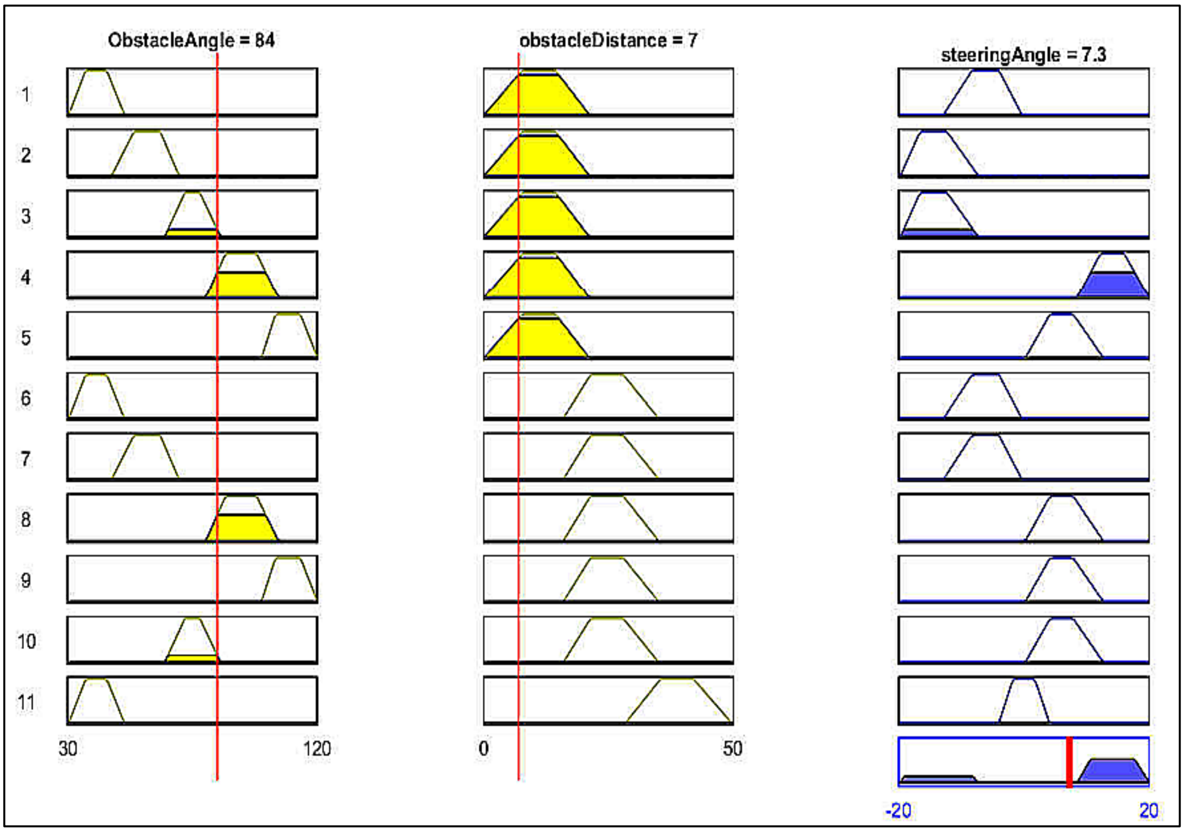


Fig 17 MATLAB Simulation Rule Viewer for the ODAS (b)

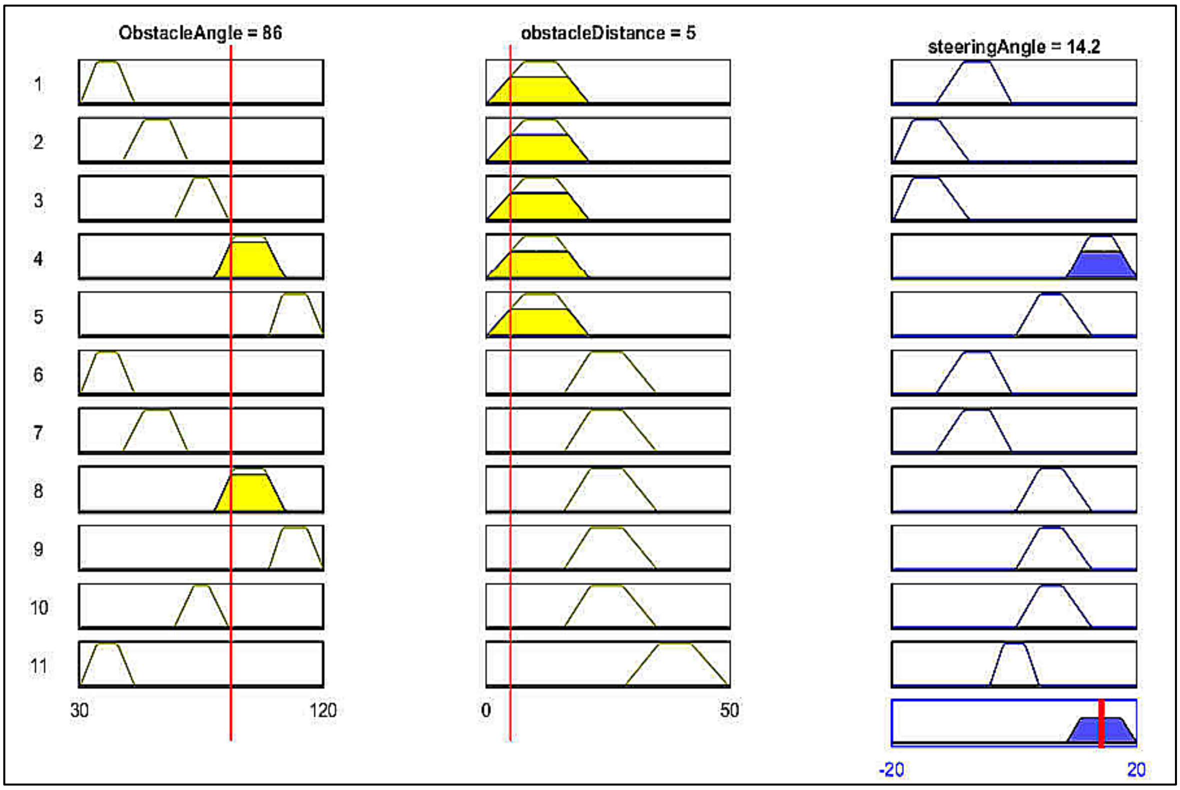


Fig 18 MATLAB Simulation Rule Viewer for the ODAS (C)

This study introduces a real-time obstacle detection and avoidance system tailored for indoor autonomous robots. To address certain limitations identified in the review of related work, we established specific objectives. Notably, we sought to resolve issues highlighted in two key publications, namely [21] and [22].

One of the primary challenges we tackled was the problem of interference associated with the use of multiple ultrasonic sensors. In response, we proposed the concept of a servo sweep. Figure 13 illustrates the impressive coverage achieved by the servo sweep, encompassing a wide viewing angle ranging from 200 to 1200 units. Within this angle, the robot is capable of detecting and effectively avoiding obstacles. Importantly, this approach eliminates the need for the robot to possess prior knowledge of obstacle locations, rendering it highly adaptable.

Another critical aspect we considered was the estimation of the system's response time. In the context of this study, response time refers to the duration between sending a signal to detect an obstacle and executing the necessary avoidance maneuvers, accounting for all intervening activities. [30] Provided a model for estimating the minimum response time of a robot, setting a threshold of 2 seconds. Our comprehensive simulations and real-world tests affirm that our proposed robot can promptly identify emergency obstacles within proximity and navigate them well within this established threshold. Figure 13 showcase three instances observed during real-world testing, with corresponding validations in MATLAB as demonstrated in Figure 16, 17 and 18. Particularly, when the robot is situated at a distance of approximately 45cm and an angle of $64^{o}$ degree (equivalent to a forward-facing orientation), it maintains a straight trajectory, as illustrated in Figure 16. Furthermore, results from Figure 13(b) and Figure 13(c), corresponding to MATLAB validations in Figure 17 and Figure 18, exhibit two instances where robot steering alternates between negative and positive values. The dynamic steering control, facilitated by the differential wheel drive and the fuzzy algorithm, enables rapid changes in direction, contributing to the robot's agile navigation capabilities. Consequently, the synergy between the fuzzy algorithm and the differential wheel drive empowers the robot with exceptional sensitivity, enabling seamless navigation within complex environments characterized by walls and scattered obstacles, as exemplified in the real-world test showcased in Figure 13(a, b, and c).

Regarding the detection of small obstacles, Figure 8 provides insight into the fuzzy classification of possible obstacle heights and surface elevations. Differing from the PID model employed by [22], our implemented fuzzy algorithm accommodates the full spectrum of potential obstacle heights. Moreover, the defuzzification method we employed, specifically the min-max approach, effectively resolves any ambiguities that may arise when an obstacle height corresponds to multiple membership functions, ensuring precise obstacle classification.

## V. CONTRIBUTION AND NOVELTY

This paper's primary contribution lies in the development and implementation of a comprehensive real-time obstacle detection and avoidance system tailored for indoor autonomous robots. While addressing this, we

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acknowledge the need to explicitly articulate the distinctive and innovative aspects of our work.

➢ *In Terms of Novelty, Our Contribution Stems from Several Key Areas:*

- Comprehensive Solution: Our proposed system offers a holistic solution to the pervasive challenge of indoor obstacle detection and avoidance for autonomous robots. We have integrated a servo sweep concept, a robust fuzzy algorithm, and a differential wheel drive mechanism to provide a comprehensive and efficient means of navigating complex indoor environments.
- Interference Mitigation: One of our novel contributions is the introduction of the servo sweep, which effectively tackles interference issues associated with the use of multiple ultrasonic sensors. This innovative approach greatly enhances the robot's adaptability in dynamic indoor settings.
- Rapid Response: We have assessed and demonstrated the system's impressive response time, exceeding the threshold set by existing models. The ability to promptly identify and navigate obstacles, even in emergency situations, constitutes a noteworthy advancement.
- Height Classification: Our fuzzy algorithm for obstacle height classification presents a departure from traditional PID models. It accommodates the entire spectrum of potential obstacle heights and employs a defuzzification method, namely min-max, to ensure precise height of categorization.
- Comprehensive Validation: We have conducted rigorous real-world testing and comprehensive MATLAB simulations to substantiate the effectiveness of our approach, providing empirical evidence of its viability.

In summary, our paper bridges a crucial gap in the field of indoor autonomous robotics by offering a novel, integrated, and efficient solution to obstacle detection and avoidance. Our system's potential benefits include enhanced adaptability, rapid response in critical scenarios, and precise obstacle height classification. These contributions collectively advance state-of-the-art in indoor robotic navigation, opening doors to improved performance and safety in various applications, such as manufacturing, logistics, and home automation.

## VI. COMPARATIVE ANALYSIS WITH EXISTING WORKS

Here, we aim to address this by summarizing the methodologies, results, and limitations of prominent prior works in the field of indoor autonomous robot obstacle detection and avoidance.

➢ *Existing Methodologies:*

[21] This approach relies on ultrasonic array-based obstacle detection and localization for auto parking systems. It utilizes four ultrasonic sensors to detect ground obstacles and employs a threshold-based distance segmentation technique. However, it is susceptible to interference among echo signals from obstacles.

[22] This work employs a frequency-modulated continuous wave (FMCW) radar sensor placed in front of a rover to estimate obstacle height based on Doppler shift. While it's less prone to interference and blind spots, it relies on a spatial model that may not capture the fuzzy nature of obstacle height.

[20] Utilizes a stereo camera system and neural networks for obstacle height measurement in intelligent home service robots. While it offers fast detection, it experiences height measurement errors with increasing distance due to image noise.

➢ *Results and Limitations*

[21] The approach successfully addresses the blind spot issue but is vulnerable to signal interference among the sensors. This affects the accuracy of obstacle detection.

[22] The FMCW radar system is effective in mitigating interference and blind spots, but it may provide irregular obstacle height estimates when dealing with non-standard obstacle shapes.

[20] Achieves fast obstacle detection but experiences increasing height measurement errors at greater distances due to image noise, potentially impacting accuracy.

➢ *Advantages of Our Approach*

In comparison to these existing methodologies, our proposed system offers several advantages:

- Interference Mitigation: Unlike [21], our servo sweep concept effectively mitigates interference issues, enhancing the robot's adaptability.
- Height Classification: In contrast to [22], our fuzzy algorithm accommodates all potential obstacle heights, ensuring precise height categorization even for irregularly shaped obstacles.
- Rapid Response: Our system demonstrates a faster response time in comparison to existing models, exceeding the threshold set by [30].
- Comprehensive Validation: We have provided extensive real-world testing and MATLAB simulations, offering empirical evidence of our approach viability, which is not present in the discussed prior works.

➢ *Limitations of Our Approach*

It is important to acknowledge some limitations of our system:

- Sensitivity to Servo Angle Calibration: The accuracy of obstacle detection can be influenced by the precise calibration of servo angles.
- Dependency on Sonar Technology: Our system relies on sonar sensors, which may introduce some uncertainty in obstacle distance measurements.

## VII. CONCLUSION

In conclusion, while we have identified certain advantages and limitations of our approach in comparison to existing works, further research and refinement are needed to address these limitations fully. Our system represents a significant step forward in indoor robot obstacle detection and avoidance, offering a holistic solution that balances accuracy, adaptability, and rapid response.

## REFERENCES

[1]. Ali Vahidi, Amir Eskandarian, "Research advances in Intelligent Collision Avoidance and Adaptive Cruise Control", IEEE Transactions on Intelligent Transportation Systems, vol. 4, no. 3, pp. 143-153, 2003. DOI: 10.1109/TITS.2003.821292

[2]. Farid Bounini, Denis Gingras, Vincent Lapointe, Herve Pollart, "Autonomous Vehicle and Real-Time Road Lanes Detection and Tracking", in IEEE Conference on Vehicular Power and Propulsion (VPPC), Montreal, 2015, pp. 1-6.

[3]. Geetha Kiran A, Murali S, "Automatic Hump Detection and 3D View Generation from a Single Road Image", in IEEE International Conference on Advances in Computing, Communications and Informatics (ICACCI), New Delhi, 2014, pp. 2232-2238. DOI: 10.1109/ICACCI.2014.6968590

[4]. Wei Lun Xu, Siu Kwan Tso, Yun Hui Fung, "Sensor-Based Reactive Navigation of a Mobile Robot through Local Target Switching", IEEE Transactions on Systems, Man and Cybernetics, Part C, vol. 29, no. 3, pp. 451-459, 1999. DOI: 10.1109/ICAR.1997.620207

[5]. Seok Joo Song, Youngmoon Moon, Dong Hwa Lee, Chang Bum Ahn, Yuntae Jo, Jangmyung Choi, "Comparative Study of Fuzzy PID Control and Fuzzy Logic-Based Control for Autonomous Vehicle: A Survey of Algorithms for Enhanced Position Control in Laparoscopic Surgery Robot", Journal of Medical and Biological Engineering, vol. 35, no. 1, pp. 34-44, 2015. DOI: 10.1007/s40846-015-0003-1

[6]. Ali Touran, Mark Brackstone, Mark McDonald, "A Collision Model for Safety Evaluation of Autonomous Intelligent Cruise Control", Accident Analysis and Prevention, vol. 31, pp. 567-578, 1999.DOI: 10.1016/S0001-4575(99)00013-5

[7]. Roberto Manduchi, Alberto Castano, A. Talukder, Larry Matthies, "Obstacle Detection and Terrain Classification for Autonomous Off-Road Navigation", Autonomous Robot, vol. 18, pp. 81-105, 2005. DOI: 10.1023/B:AURO.0000047286.62481.1d

[8]. Amit Konar, Indrani Goswani Chakraborty, Sapam Jitu Sirya, Lakhmi C. Jain, Atulya K. Nagar, "A Deterministic Improved Q-Learning for Path Planning of a Mobile Robot", IEEE Transactions on Systems, Man and Cybernetics, vol. 43, no. 5, pp. 1141-1153, 2013. DOI: 10.1109/TSMCA.2012.2227719

[9]. Jayasree Chakraborty, Amit Konar, Lakhmi C. Jain, Uday Kumar Chakraborty "Cooperative Multi-Robot Path Planning Using Differential Evolution", Journal of Intelligent and Fuzzy Systems, vol. 20, no. 1-2, pp. 13-27, 2009. DOI: 10.3233/IFS-2009-0412

[10]. Othmane Hachour, "Path Planning of Autonomous Mobile Robot", International Journal of Systems Applications, Engineering and Development, vol. 2, no. 4, pp. 178-190, 2008.

[11]. Peter Stone, Mohan Sridhar, Daniel Stronger, Gregory Kuhlmann, Nate Kohl, Peggy Fidelman, Nicholas K. Jonga, "From pixels to multi-robot decision-making: A study in uncertainty," Robotics and Autonomous Systems, vol. 54, no. 11, pp. 933-943, 2006. DOI: 10.1016/j.robot.2006.05.010

[12]. Antonio Sgorbiss, Renato Zaccaria, "Planning and Obstacle Avoidance in Mobile Robotics", Robotics and Autonomous Systems, vol. 60, no. 4, pp. 628-638, 2012. DOI: 10.1016/j.robot.2011.12.009

[13]. Bernard I. Hartman, Yasuhiro Kanayama, Thomas Smith, "Model and Sensor Based Preside Navigation by an Autonomous Vehicle", Advanced Robotics, vol. 3, pp. 98-109, 1989.

[14]. Ravi Lagisetty, Nirmal K. Philip, Raghavendra Padhi, M. S. Bhat, "Object Detection and Obstacle Avoidance for Mobile Robot Using Stereo Camera", in IEEE International Conference on Control Applications (CCA), Hyderabad, 2013, pp. 605-610. DOI: 10.1109/CCA.2013.6662816

[15]. Mehran Norouzi, Ali Karambaskhsh, Milad Namazifar, Branislav Savkovic, "Object Obstacle Based Navigation of Mobile Robot with Obstacle Avoidance using Fuzzy Controller", in IEEE International Conference on Control and Automation, Christchurch, 2009, pp. 169-174. DOI: 10.1109/ICCA.2009.5410407

[16]. Bayanjargal Baasandorj, Aamir Reyaz, Park Joung Ho, Cha Wang Cheol, Deokjin Lee, Kil To Chong "A Mobile Robot Obstacle Avoidance Using Fuzzy Logic and Model Predictive Control", Applied Mechanics and Materials, pp. 922-927, 2014. DOI: 10.4028/www.scientific.net/AMM.548-549.922

[17]. H.R. Beom, Hyungsuck Cho, "A Sensor-Based Obstacle Avoidance Controller for a Mobile Robot using Fuzzy Algorithm and Neural Network", in IEEE Proceeding of the International Conference on Intelligent Robots and Systems, 1992, pp. 1470-1475. DOI: 10.1109/IROS.1992.594576

[18]. Neal E. Hodge, Mohamed B. Trabia, "Steering Fuzzy Logic Controller for an Autonomous Vehicle", in Proc. of IEEE International Conference on Robotics and Automation: Detroit, Michigan, 1999, pp. 2482-2488. DOI: 10.1109/ROBOT.1999.770478

[19]. Wei Lun Xu, Siu Kwan Tso, Yun Hui Fung, "Sensor-Based Reactive Navigation of a Mobile Robot through Local Target Switching", in IEEE Transaction on Systems, Man and Cybernetics, Part C, vol. 29, no. 3, pp. 451-459, 1997. DOI: 10.1109/ICAR.1997.620207

[20]. Feroz Ahmed Siddiky, Mohammed Shamsul Alam, Tanveer Ahsan, "High-Performance Reliable Obstacle Detection and Height Measurement by Stereo Camera for Intelligent Home Service Robot", in Proc. of IEEE 10th International Conference on Computer and

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr115

Information Technology, Dhaka, 2007, pp. 1-6. DOI: 10.1109/ICCITECHN.2007.4579364
[21]. Huihai Cui, Jinze Song, Daxue Liu, "Ultrasonic Array Based Obstacle Detection in Automatic Parking", Proceedings of 2013 Chinese Intelligent Automation Conference. Lecture Notes in Electrical Engineering, vol 255. Springer, Berlin, Heidelberg. 2013, pp. 129-140 https://doi.org/10.1007/978-3-642-38460-8_15.
[22]. Zhang Hongping, Liu Quanbo, Chen Wenliang, Sun Fe, Chen Dapeng, "Doppler Shift and Height Detection of Obstacle Based on FMCW Radar Sensor", in Proc. of IEEE International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery, Xi'an, China, 2015, pp. 399-402. DOI: 10.1109/CyberC.2015.64
[23]. Pierrick Grandjean, Larry Matthies, "Perception Control for Obstacle Detection by a Cross-Country Rover", In Proceeding of IEEE International Conference on Robotics and Automation, Atlanta, 1993, pp. 20-27. DOI: 10.1109/ROBOT.1993.292118
[24]. Stefan Baten, Michael Lützeler, and Ernst D. Dickmanns, "Techniques for autonomous, off-road navigation", IEEE Intelligent Systems Magazine, pp. 57–65, 1998. DOI: 10.1109/5254.736003
[25]. Alonzo Kelly, "An Intelligent Predictive Control Approach to the High-Speed Cross-Country Autonomous Navigation Problem", Carnegie Mellon Robotics Institute, Ph.D. Thesis CMU-RI-TR-95-33, 1995.
[26]. John Hancock, "High-Speed Obstacle Detection for Automated Highway Applications", Carnegie Mellon Robotics Institute Technical Report, CMU-RI-TR-97-17, 1997.
[27]. Johann Borenstein, Yoram Koren, "Obstacle Avoidance with Ultrasonic Sensors", International Journal of Robotics and Automation, vol. 4, no. 2, pp. 213-218, 1988. DOI: 10.1109/56.2085
[28]. Azeta Joseph, Christian Bolu, Daniel invi, Abiodun Abioye, "Obstacle detection using an ultrasonic sensor for a mobile robot," IOP Conf. Series: Materials Science and Engineering, vol. 707, 2019, 012012. DOI 10.1088/1757-899X/707/1/012012
[29]. Jianwei Zhao, Jianhua Fang, Shouzhong Wang, Kun Wang, Chengxiang Liu, Tao Han, "Obstacle Avoidance of Multi-Sensor Intelligent Robot Based on Road Sign Detection", Sensors, vol. 21, no. 20, 6777, 2021. DOI: https://doi.org/10.3390/s21206777
[30]. Aldis Baums, Gordyushin, A. "Response time of a mobile robot", Automatic and Control Computer Science 47, 352–358 (2013). DOI: 10.3103/S0146411613060023.
[31]. Martin Dekan, František Duchoň, Ladislav Jurišica, Anton Vitko and Andrej Babinec, "iRobot Create Used in Education," Journal of Mechanical Engineering and Automation, vol. 3, no. 4, pp. 197-202, 2013. DOI:10.17265/2159-5275/2013.04.002
[32]. Tauã M. Cabreira, Gracaliz P. Dimuro, Marilton S. de Aguiar, "An Evolutionary Learning Approach for Path Planning with Fuzzy Obstacle Detection and Avoidance in a Multi-Agent Environment," in IEEE third Brazilian Workshop on Social Simulation, Brazil, 2012, pp. 60-67. DOI Bookmark: 10.1109/BWSS.2012.13
[33]. Hau-Shiue Juang, Kai Yew Lum, "Design and control of a two-wheel self-balancing robot using the Arduino microcontroller board," in Proc. of IEEE 10th International Conference on Control and Automation (ICCA), pp. 634 - 639, 12-14 June 2013. Date Added to IEEE Xplore: 22 July 2013. DOI: 10.1109/ICCA.2013.6565146
[34]. André Araújo, David Portugal, Micael S. Couceiro, Rui P. Rocha, "Integrating Arduino-Based Educational Mobile Robots in ROS," Journal of Intelligent & Robotic Systems, vol. 77, no. 2, pp. 281-298, 2020. DOI: 10.1007/s10846-013-0007-4

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