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ENHANCING NAVIGATION FOR THE VISUALLY IMPAIRED: A MAMDANI TYPE 1 FUZZY LOGIC APPROACH TO OBSTACLE DETECTION

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Abstract

The traditional white cane though commonly used by the visually impaired only has little usability in the complex and dynamic environment. Most previous research has focused on image detection algorithms for assistive devices, but they are less reliable in poor visibility and sensitive to environmental conditions. This study proposes an innovative solution through the combination of haptic feedback with a Fuzzy Logic Controller (FLC) for the better detection of obstacles and user notification. The proposed system incorporates MATLAB applications that enables the vibration intensity to be adjusted depending on the distance and direction of the obstacles and is more convenient for the user compared to the traditional methods. This work is new in the sense that it uses distance and direction as the two inputs in the fuzzy controller, which uses six fuzzy rules to control the vibration speed and direction of the actuator. This fine-tuned control allows the user to clearly identify the distance and location of the obstacles. The system's performance was validated with a root-mean-square-error (RMSE) of 0.568, which indicates a high level of accuracy in the model's predictions. This low RMSE is the result of small difference between the predicted and real obstacle distances and directions and proves that the system is reliable providing accurate feedback in real-life situations. Thus, this contribution is a valuable improvement in the field of assistive technologies for visually impaired, providing a more effective means for navigation by the visually impaired.

Keywords: Assistive technology, Fuzzy logic controller, Haptic feedback, Visual impairment.

1. Introduction

Visual impairment refers to a condition that significantly reduces an individual's ability to see clearly, limiting both visual acuity and range. It encompasses a broad spectrum of vision loss, from mild difficulties to complete blindness, affecting individuals of all ages globally [1]. According to the World Health Organization (WHO), around 2.2 billion people worldwide have some form of visual impairment, with nearly 1 billion cases preventable or yet to be addressed [2]. Alarmingly, over 80% of these cases could be effectively treated, highlighting the importance of awareness, accessible healthcare, and preventative eye care. Apart from its effect on daily activities, Bonsaksen, Brunes and Heir [3] said visual impairment affects educational opportunities, employment potential, and overall quality of life. Understanding the causes, implications, and accommodations for visual impairment is crucial in fostering inclusivity and support for those navigating this challenge.

Despite technological advancements, existing navigation systems for visually impaired individuals often fall short of providing comprehensive support. Traditional aids like white canes and guide dogs remain the primary tools for navigating obstacles and surface inconsistencies. However, Isazade [4] explains white canes are limited to detecting ground-level hazards, leaving higher obstacles undetected, while Trybocka [5] highlights guide dogs may not fully interpret complex environments. Additionally, Zhang et al. [6] point out Visually impaired individuals also rely on non-visual cues, such as auditory and tactile feedback, which can be insufficient in dynamic or complex settings.

Given these limitations, the development of Electronic Travel Aids (ETAs) that integrate advanced sensors and algorithms has become crucial for improving mobility and safety for visually impaired individuals. Recent technological have introduced novel devices, such as obstacle detectors, which use cutting-edge sensors to provide real-time feedback, offering blind individuals greater independence and safety in their daily movements. Among the technologies explored, artificial intelligence (AI) and sensor integration play a crucial role in improving the effectiveness of ETAs.

Traditional aids, such as white canes, rely on physical contact with obstacles, which can be limiting, particularly for higher or distant obstacles, as dos Santos et al. [7] points out. This underscores the need for sensors capable of detecting obstacles at various heights and distances, such as Ultrasonic, LiDAR and Cameras. For example, Basheshankar et al. [8] describes smart canes use ultrasonic sensors to detect obstacles and provide voice feedback, while Bleaue et al. [9] discusses cognitive guidance systems rely on RGB Camera, such as Kinect sensors, coupled with voice feedback. Our device, however, uses a LiDAR sensor to detect obstacles, providing haptic feedback to the user for a more intuitive and less intrusive experience in complex environments. Selecting the right sensor is vital to ensure that visually impaired users receive accurate and timely feedback. LiDAR and ultrasonic sensors are two common choices in assistive technologies, but they differ greatly in terms of functionality.

LiDAR sensors use laser pulses to calculate the distance, position, and shape of surrounding objects, as Alam and Oluoch [10] explains. This technology offers a higher range of detection and superior obstacle recognition, making it more suitable for dynamic environments where precision in real-time navigation is critical, according to Wang et al. [11]. On the other hand, ultrasonic sensors, which emit sound waves and measure their return time, are typically cheaper, as noted by Aliew [12] and are often found in more basic applications like smart canes. However, Win et al. [13] highlights ultrasonic sensors are limited in their range and resolution, making them less capable of detecting small or thin objects or providing detailed spatial awareness. In more intricate or fast-changing environments, ultrasonic sensors may fall short of the necessary precision for effective navigation, as Sze et al. [14] points out.

While many recent assistive technologies incorporate artificial intelligence using computer-vision algorithms such as CNN, as noted by Ahmed et al. [15], YOLO, highlighted by Oleiwi and Kadhim [16], and Vision-based SLAM, discussed by Chen et al. [17], this project explores a different approach by using LiDAR as the primary sensor in combination with a fuzzy logic controller, another element of artificial intelligence. The use of LiDAR technology presents a unique advantage over computer vision in terms of processing speed and the ability to operate effectively in varying light conditions, as YellowScan [18] points out. This approach raises a crucial question: How effectively can integrating a fuzzy logic controller with LiDAR technology enhance real-time obstacle detection and haptic feedback for visually impaired individuals? To better understand the benefits of this approach, it's essential to consider the inherent limitations of existing computer-vision algorithms.

Computer-vision algorithms process large volumes of visual data to identify, classify, and track objects in the environment. For instance, Al Abir et al. [19] explains YOLO v5 can detect objects in real time with high precision and detailed visualization, making it applicable for tasks such as object detection and scene analysis as discussed by Bispo [20] and Oluyele et al. [21] However, He et al. [22] notes the reliance on visual data in these systems makes them susceptible to environmental factors such as lighting, shadows, and occlusions, leading to inconsistent performance, especially in low-light scenarios. Furthermore, Voulodimos et al. [23] highlights computer vision systems are computationally intensive, and their high processing demand may not be optimal for applications requiring fast and energy-efficient responses.

To address these limitations, our system utilizes a Fuzzy Logic Controller, which excels in handling uncertainty and ambiguity, making it ideal for applications like walking guidance for the visually impaired, as noted by Scott [24]. Unlike traditional Boolean logic, which operates on binary values (True or False), as explains by Astels [25], Fuzzy Logic allows for intermediate states, enabling more flexible and human-like decision-making, according to Nica et al. [26]. This is particularly valuable in environments where sensor data may be unclear or incomplete, as Fuzzy Logic can interpret such data and generate more reliable outputs. This approach provides a more adaptable and energy-efficient solution compared to computationally heavy vision systems.

In this research, fuzzy logic is applied to obstacle detection, where the system adjusts the intensity of haptic feedback based on the proximity and type of obstacles. One key benefit is that fuzzy logic controllers are less computationally demanding compared to sophisticated computer vision systems, enabling faster response times while conserving energy, as points out by Zhu et al. [27]. Riman and Abi-Char [28] explained these controllers are flexible, scalable, and offer greater adaptability to real-world conditions, making them well-suited for enhancing navigation aids for visually impaired individuals. Fuzzy logic has been successfully applied in various assistive technologies for visually impaired individuals. For instance, some ETAs utilize multiple LiDAR sensors in combination with fuzzy logic to provide multi-directional obstacle detection and guidance, as highlighted from Bouteraa[29].

While existing ETAs incorporate multiple sensors with Fuzzy Logic to provide obstacle detection from several angles, as noted by Tayyaba and Ashraf [30], this project utilizes a single RPLIDAR which is 2D LiDAR, capable of scanning a 360-degree field of view. The RPLIDAR's comprehensive scanning ability reduces the need for multiple sensors while still providing accurate and real-time spatial perception. Moreover, by combining this with a fuzzy logic controller, this system delivers efficient and fast obstacle detection without the computational complexity typically associated with multi-sensor setups. Ultimately, this combination of RPLiDAR and fuzzy logic offers a streamlined, efficient, and adaptable solution for real-time obstacle detection and navigation, providing users with a more reliable and responsive assistive technology.

The novelty of this study lies in its distinctive approach to enhancing obstacle detection for visually impaired individuals by controlling the haptic feedback motor through the integration of 2D LiDAR technology and a fuzzy logic controller (FLC). This system's primary job is to identify obstacles and alert the user using the appropriate sensors that offer information to those with low eyesight. When an obstacle is present, a RPLiDAR sensor connected to the system can detect it and be controlled by fuzzy logic to alert the user using haptic feedback and allow them to go safely till they reach their destinations. However, the applications of this work extend beyond the prototype presented in this study. For example, the system can be integrated into wearable technologies, assisting not only visually impaired users but also individuals navigating unfamiliar environments or hazardous conditions. These applications demonstrate the broader relevance of our findings to enhancing safety and accessibility in a variety of real-world contexts.

The primary aim of this study is to develop and evaluate a fuzzy logic controller integrated with a 2D LiDAR-based obstacle detection device to provide real-time, precise haptic feedback for visually impaired users. By applying the Mamdani method of fuzzy inference within MATLAB's fuzzy toolbox, the study adjusts vibration intensity based on obstacle proximity as shown in Fig. 1.

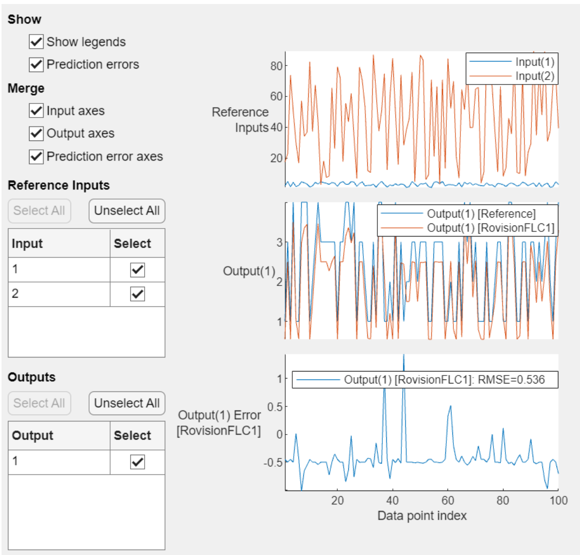


Fig. 1. Fuzzy logic controller in MATLAB platform.

The effectiveness of the fuzzy logic controller is validated through performance metrics, including the root-mean-square-error (RMSE), which demonstrates the system's precision and practical applicability. This research contributes to the field of assistive technologies by offering a more accurate and responsive navigation aid for visually impaired individuals.

2. System Description

Individuals with visual impairments encounter numerous challenges in their daily routines, including navigating within their homes due to obstacles obstructing their paths. A dependable obstacle detection system serves as a crucial aid, ensuring safe mobility in familiar and unfamiliar settings by identifying and avoiding surrounding objects. Figure 2 depicts the block diagram of the obstacle detection system.

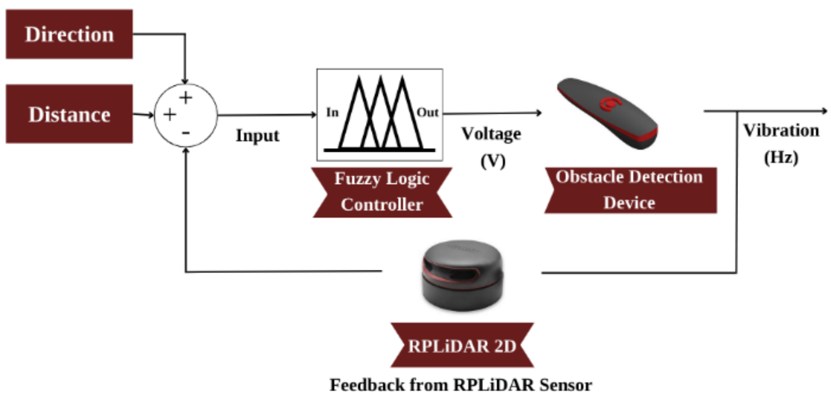


Fig. 2. Block diagram of obstacle detector.

This system relies on two inputs to enable Fuzzy Logic processing and generates a voltage output, which is then transmitted to the assistive device. This voltage level serves as haptic feedback to notify the user of safe navigation conditions. The system employs a LiDAR sensor to detect objects and generate input signals, including direction and distance information.

3. Proposed Fuzzy Based Obstacle Detection

A controller for a robotic guide must be capable of managing the current nonlinear trends and corresponding uncertainty While Boolean controllers are commonly used in industrial settings, an argument can be made for the superiority of fuzzy logic controllers due to their emulation of human cognition. Fuzzy logic encompasses truth values beyond the binary 0 and 1, incorporating various intermediate levels of truth rather than strict binary states. Based on fuzzy set theory, the fuzzy logic inference system (FIS) models complex nonlinear issues.

Fuzzy logic control, which was widely adopted in many real-time applications, was developed to increase and optimise a system's performance. A fuzzy logic framework has 4 main components as illustrates in Fig. 3.

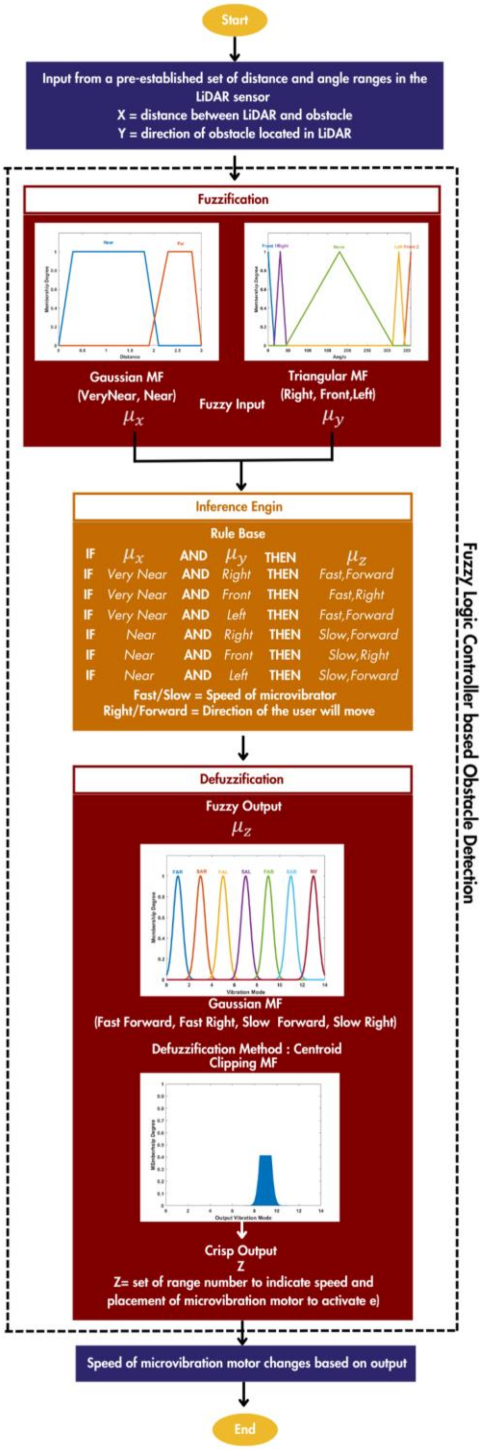


Fig. 3. Flow chart of the proposed FLC based obstacle detection for visually impaired navigation enhancement.

3.1. Fuzzification

It is a method for transforming an exact set of numbers into an approximate set of numbers. It is necessary to declare all well-known, distinct, and predictable quantities to be completely deterministic and extremely uncertain in order to achieve this. This uncertainty may have arisen as a result of the inherent fuzzyness and imprecision of the variables, which resulted in their being stated as a membership function. A membership function (MF) is a graphical representation of any value's degree of membership in a specified fuzzy set. The X-axis of the graph denotes the scope of discourse, while the Y-axis denotes the degree of membership in the [0, 1] range.

There are 13 types of membership function integrated into the Fuzzy Logic Toolbox which are triangular, gaussian, trapezoidal, sigmoid, linear z-shaped, linear s-shaped, z-shaped, generalized bell, different sigmoids, pi-shaped, two-sided Gaussian and product sigmoids. The type of membership functions used in this research were Triangular and Gaussian. The membership function of the inputs and outputs has been varied and results is shown in section 3.

This FLC simulation process consists of 2 inputs and 1 output. The first input is the distance between the obstacle detector and the object while the second input is the direction of the obstacle located. The output parameter is in form of the speed of vibration and direction for user to follow.

The range of the parameter for the first input is between 0-5 metres since WHO has stated that the maximum distance for visually impaired can see is within 4m and it varies depending on many different factors [1]. As illustrated in Fig. 4, the initial inputs were represented by 2 membership functions (MFs), and for the subsequent inputs, there were 3 MFs, whereas the output comprised 4 MFs. The first set of inputs was defined by membership functions label as 'Very Near (VN)' and 'Near (N).' The two linguistic values for the variable *distance:*

{Very Near, Near}

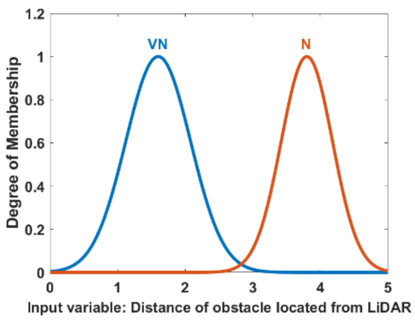


Fig. 4. Input variable for obstacle distance.

$$\mu_{VeryNear}(X; 0.48, 1.6) = e^{-\frac{1}{2}\left(\frac{X-0.48}{1.6}\right)^2} \quad (1)$$

$$\mu_{Near}(X; 0.38, 3.8) = e^{-\frac{1}{2}\left(\frac{X-0.38}{3.8}\right)^2} \quad (2)$$

For the second output, the range is between 0-90° in which 0-30° is when the obstacle located at the right side of the system, 30-60° for the front side and 60-90° for the obstacle in the left side. The output range is between 0-4 which represent switch function when the sensor detects the obstacle. MFs to represent the second input were Right (R), Front (F)and Left (L) as shown in Fig. 5. The two linguistic values for the variable direction:

{Right, Front, Left}

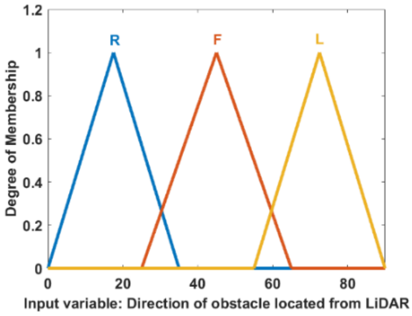


Fig. 5. Input variable for obstacle position.

$$\mu_{Right}(Y; 0.17.5, 35) = \begin{cases} 0 & Y \leq 0 \\ \frac{Y}{17.5} & 0 < Y \leq 17.5 \\ \frac{35-Y}{17.5} & 17.5 < Y \leq 35 \\ 0 & Y > 35 \end{cases} \quad (3)$$

$$\mu_{Front}(Y; 0.17.5, 35) = \begin{cases} 0 & Y \leq 25 \\ \frac{Y-25}{45} & 25 < Y \leq 45 \\ \frac{65-Y}{20} & 45 < Y \leq 65 \\ 0 & Y > 65 \end{cases} \quad (4)$$

$$\mu_{Left}(Y; 0.17.5, 35) = \begin{cases} 0 & Y \leq 55 \\ \frac{Y-55}{72.5} & 55 < Y \leq 72.5 \\ \frac{35-Y}{17.5} & 72.5 < Y \leq 90 \\ 0 & Y > 90 \end{cases} \quad (5)$$

3.2. Fuzzy inference

Fuzzy inference system focuses primarily on decision-making This is the core element of a fuzzy logic system. It uses the "IF...THEN" rules and the connectors "OR" or "AND" to create the important decision rules.

Once the crisp input undergoes fuzzification, it aligns with the fuzzy sets within the related atomic fuzzy propositions of each rule's antecedent, thereby assigning a degree of satisfaction to each individual atomic proposition. Based on the rule, the inferred output will be provided. Figure 6 shows is the Gaussian MFs of the output parameter which the universe of discourse are [0,4]. The four linguistic values for the variable *Output:*

{Fast Front, Fast Right, Slow Front, Slow Right}

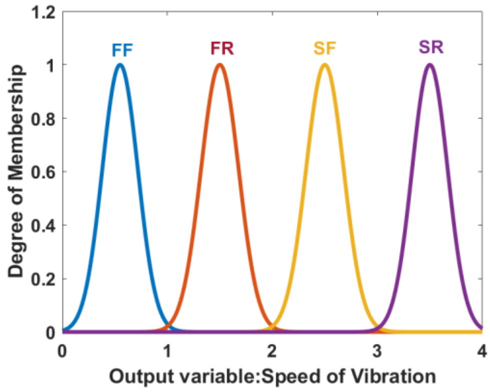


Fig. 6. Output variable parameter.

The MFs corresponding to the linguistic values are represented by the following Gaussian fuzzy numbers:

Fast Front = (0.17,0.55)
Fast Right = (0.18 1.5)
Slow Front = 0.18 2.5)
Slow Right = (0.17 3.5)

3.3. Knowledge base

3.3.1. Data base

The database plays a crucial role in providing necessary information needed for the smooth functioning of various modules within the inference engine, such as fuzzification, reasoning, and defuzzification. It contains the membership functions for fuzzy sets representing linguistic values across different linguistic variables. These functions assign importance to the linguistic variables and values used within the rule sets, enhancing their significance.

3.3.2. Rule base

The rule bases which are the set of rules that were created with by specify the antecedents and the consequents. The rules in this paper were interpreted using Mamdani. To implement the fuzzy controller in the system, six rule bases are needed, corresponding to three membership functions for one input and two membership functions for the other input. These rule bases can be represented as tables measuring 3×2 in size for visualization.

R_i : IF x is A_i AND y is B_i THEN z is C_i, i=1,2,n
R_1: IF Distance is VN AND Direction is Right THEN Output is FF
R_2: IF Distance is VN AND Direction is Front THEN Output is FR
R_1: IF Distance is VN AND Direction is Left THEN Output is FF
R_1: IF Distance is N AND Direction is Right THEN Output is SF
R_1: IF Distance is N AND Direction is Front THEN Output is SR
R_1: IF Distance is N AND Direction is Left THEN Output is SF

3.4. Defuzzification

It is fuzzification's opposite. In the former, crisp results were transformed into fuzzy results, while in this instance, a mapping technique is employed to convert fuzzy outcomes back into crisp ones. This method allows for creating a clear control action that represents the likelihood distribution of an inferred fuzzy control action. Defuzzification, akin to rounding off, condenses a fuzzy set into a singular numerical value. MATLAB offers five defuzzification methods: centroid, bisector, middle of maximum (the average of the highest output set's value), largest of maximum, and smallest of maximum. The most widely utilized approach in MATLAB is centroid or Centre of Gravity (COG).

$$Z = \frac{\sum_{i=1}^{n} c_i \mu_{A_i}(x)\mu_{B_i}(y)}{\sum_{i=1}^{n} \mu_{A_i}(x)\mu_{B_i}(y)} \tag{6}$$

This research use COG method after aggregated all the possible output: z. The crisp output represented the mode and level of Vibration Motor for the haptic feedback for the user.

4. Results and Discussion

4.1. Varied membership function graph

As mentioned above in section 3.1, MATLAB has 13 built-in membership function. In order to choose the best MF for both inputs and output, this research have tried varied MF and analyse the result. Only triangular and Gaussian MF were chosen because it satisfies the universe of discourse for inputs and output.

Root-Mean-Square Error (RMSE) are calculated to each variation and the lowest value indicate that the MFs fits the data well and has more precise predictions. This study used Gaussian MF for the first input and output while Triangular MF for second input since this variation has the lowest RMSE values based on Table 1.

Table 1. Type of membership functions and RMSE.

First Input	Second Input	Output	Root Mean Square Error
Triangular	Triangular	Triangular	0.568
Triangular	Gaussian	Triangular	0.580
Gaussian	Triangular	Triangular	0.542
Gaussian	Gaussian	Triangular	0.542
Gaussian	Gaussian	Gaussian	0.537
Gaussian	Triangular	Gaussian	0.536
Triangular	Gaussian	Gaussian	0.580
Triangular	Triangular	Gaussian	0.670

4.2. Performances of the proposed method

Figure 7(a) shows fuzzification example of when the obstacle is 2.5 m away from the system and at 45° which located front of the system. Initially, the process involves taking the crisp inputs, X and Y, and evaluating their membership in the relevant fuzzy sets. This evaluation is based on the obtained Figs. 4 and 5, which is based on the Eqs. (1) and (4).

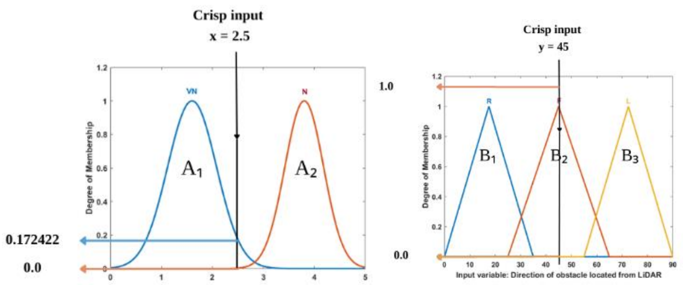
The inputs, once fuzzified, are used in the antecedents of the fuzzy rules. With two antecedents in this study, the fuzzy operator (AND) is employed to derive a singular consequent value. Assessing the conjunction of the rule antecedents involves utilizing the AND fuzzy operation intersection, as demonstrated:

$$\mu_{A\cap B}(x) = \min\{\mu_A(x), \mu_B(x)\} \quad (7)$$

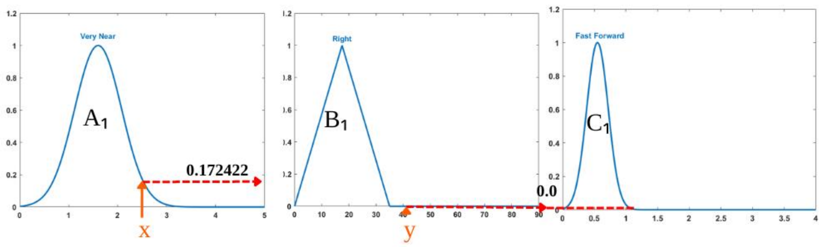
The result is given in the Fig. 7(b).

The outcome of assessing the antecedent can now be utilized with the membership function of the consequent. A prevalent approach to aligning the rule consequent with the truth value of the rule antecedent involves trimming the consequent membership function to match the level of the antecedent truth. This technique is commonly referred to as clipping as shown in Fig. 7(c).

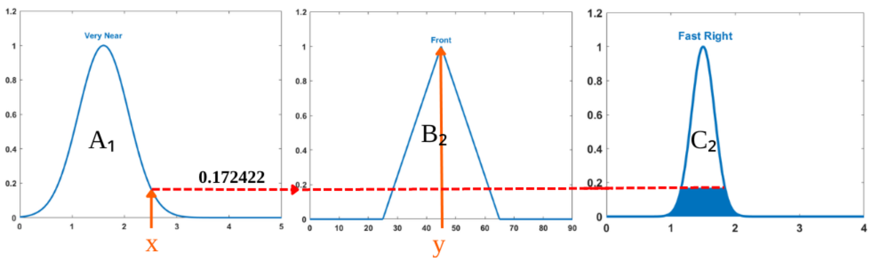
$\mu_{A_1} = 0.172422, \mu_{B_1} = 0.4444$



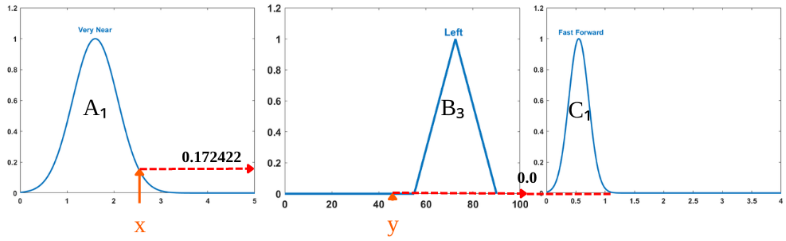
(a) Fuzzification.



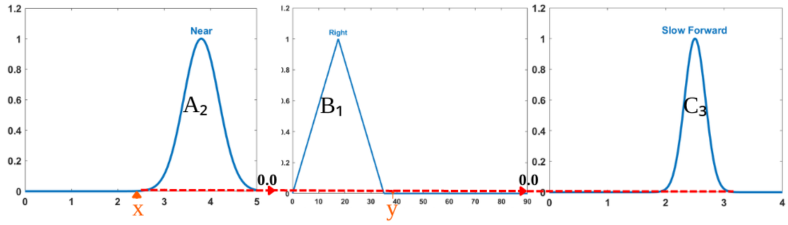
Rule1: IF x is A_1 (0.172422) AND y is B_1 (0.0) THEN z is C_1 (0.0)



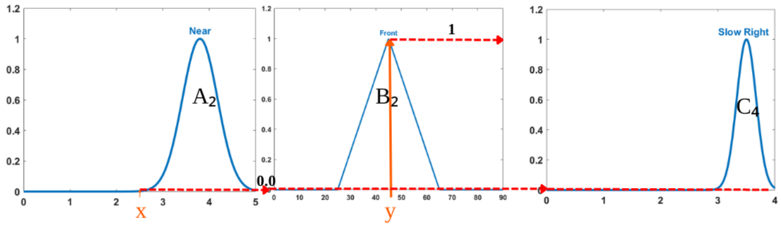
Rule2: IF x is A_1 (0.172422) AND y is B_2 (1.0) THEN z is C_2(0.172422)



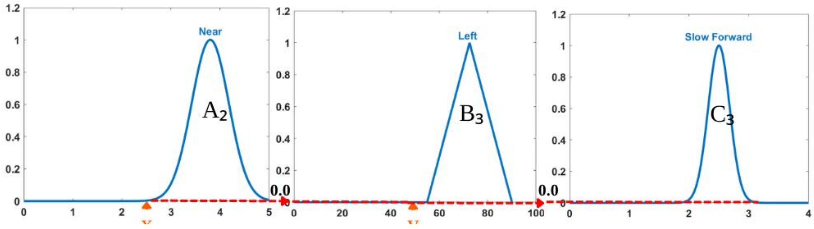
Rule3: IF x is A_1 (0.172422) AND y is B_3 (0.0) THEN z is C_1 (0.0)



Rule4: IF x is A_2 (0.0) AND y is B_1 (0.0) THEN z is C_3 (0.0)

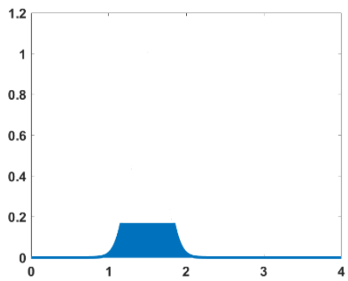


Rule4: IF x is A_2 (0.0) AND y is B_2 (1.0) THEN z is C_4 (0.0)



Rule4: IF x is A_2 (0.0) AND y is B_3 (0.0) THEN z is C_3 (0.0)

(b) Rules evaluation.



(c) Clipping.

Fig. 7. Proposed Mamdani fuzzy logic controller.

The defuzzification method used in this study is centroid technique. It finds a point representing the centre of gravity (COG). Since it only has one Gaussian output, instead of aggregated fuzzy set combine, we just have to find COG of that Gaussian.

By analogy with the geometric centroid,

$$\langle z \rangle = \frac{\int z f(z) dz}{\int f(z) dz} \tag{8}$$

where the $f(z)$ is Gaussion function, the centroid is

$$\langle z \rangle = \frac{\int_{-\infty}^{\infty} z\, e^{-\frac{1}{2}(\frac{x-m}{\sigma})^2} dz}{\int_{-\infty}^{\infty} e^{-\frac{1}{2}(\frac{x-m}{\sigma})^2} dz} = \frac{\sigma\sqrt{2\pi} z_0}{\sigma\sqrt{2\pi}} = z_0 \tag{9}$$

Based on the graph output,

$$z_0 = 1.54$$

Output range and corresponding vibration motor status is shown in Table 2. There are 2 Vibration Motors that are placed left and right of the obstacle detector. Vibration Motor 1 indicate that the user must turn right while Vibration Motor 2 specify that user must walk forward. The output gives out 1.5 which represent that the vibration of the haptic feedback must be faster, and the user should turn right slight to avoid the obstacle.

Table 2. Output range and corresponding vibration motor status.

Output range	Vibration Motor 1		Vibration Motor 2	
	Intensity level	Mode	Intensity level	Mode
0-1	HIGH	ON	OFF	OFF
1-2	OFF	OFF	HIGH	ON
2-3	LOW	ON	OFF	OFF
3-4	OFF	OFF	LOW	ON

4.3. Verification of the proposed method

For the purpose of validating the performance of the proposed FLC based obstacle detection for visually impaired navigation enhancement, 100 data points were generated based on simulated desired output that mimic the output from rplidar model A2. This lidar sensor has got the capability of pro finding dual detection in terms of distance and angle. This data resembles the sensor from range of 0-90, 0-5 respectively as shown in Figs. 8(a) and (b).

In Fig. 8(c) depicts both the validate output and the output from this study FLC. In Fig. 8(d) shows the residual which is the difference between the valid output and this FLC output. Thus, for each residual data point can be compute for the mean and take the square root out of it to calculate the root-mean-square error (RMSE).

The RMSE indicates the degree of alignment between observed data points and the model's predicted values, reflecting the model's overall fit to the data. Having 0.536 of RMSE indicates this FLC have better fit as the lower the value of RMSE, the better the model is. The FLS has +- 1.5 margin error that suggest small margin error. Additionally, a narrower margin of error signifies higher confidence in the obtained outcomes.

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(\hat{z}_1 - Z_1)^2}{n}} = \sqrt{\frac{28.73546}{100}} = 0.536055$$

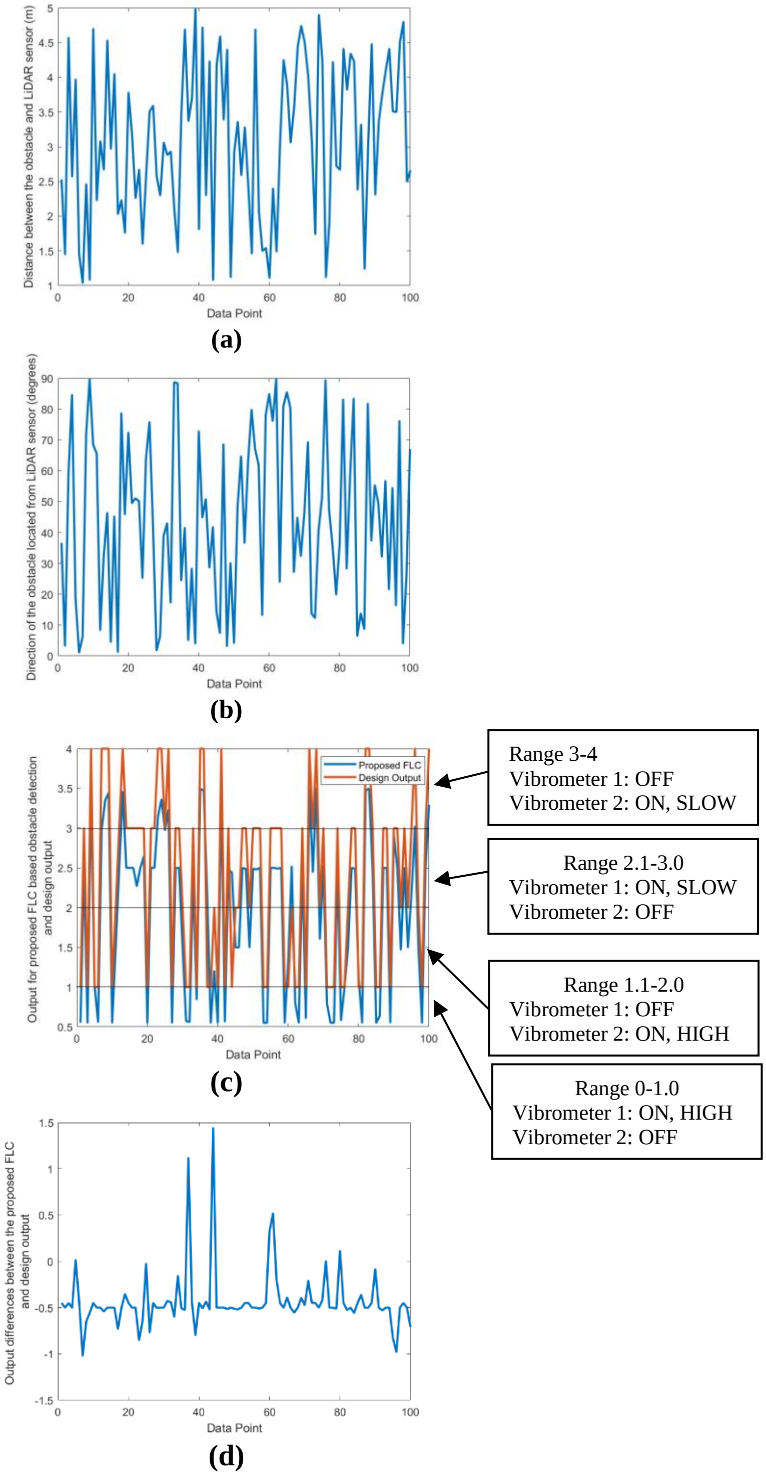


Fig. 8. System validation of proposed fuzzy logic controller.

5. Conclusions

This study presents the design and implementation of a fuzzy logic controller (FLC) based on the Mamdani method for obstacle detection in assistive navigation systems. The research describes the measures that can be taken to assess the performance of the controller and gives some information about the work of the system, including the operation of the LiDAR sensor that identifies obstacles and how the FLC changes the speed of the vibration to give feedback to the user.

MATLAB was used in the simulation and analysis of the system and thus, the fuzzy logic controller proved the theoretical and practical applicability of the FLC in real life situations where precise and timely detection of obstacles is paramount to the safety of the users and the effectiveness of the navigation aids. With an RMSE of 0.568, the FLC model performs effectively, according to the results, correctly estimating the vicinity of obstacles and offering dependable feedback.

However, the current system has certain limitations. One significant drawback is that it only detects obstacles in front of the user within a specific range, and it does not account for hazards below, such as potholes or uneven surfaces, which could pose additional risks. This limitation indicates a potential area for future enhancement, particularly in developing more comprehensive detection capabilities.

Besides that, one of the possible directions for the further improvement of the system's functionality and its performance is the use of additional sensors, for example, depth cameras or infrared sensors that can provide more data about the surroundings to enhance the recognition of obstacles and improve the accuracy of the system. Moreover, widening the number of feedback modalities, for example, using auditory or visual signals, may also improve the system's functionality and adapt it to the need of different users.

Nomenclatures

X	Crisp input for distance parameter
x	Fuzzy logic input for angle parameter
Y	Crisp input for angle parameter
y	Fuzzy logic output for vibration sensor parameter
Z	Crisp output for vibration intensity parameter
z	Fuzzy logic input for distance parameter

Greek Symbols

μ	Fuzzy sets

Abbreviations

CNN	Convolutional Neural Network
FIS	Fuzzy Inference System
FLC	Fuzzy Logic Controller
RMSE	Root-Mean-Square Error
VI	Visual Impairment
WHO	World Health Organization
YOLO	You Only Look Once

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