Research Article

REAL-TIME CONTROL OF A FIVE-DEGREE OF FREEDOM SERVICE ROBOT ARM USING TYPE-2 FUZZY LOGIC

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Abstract. *Technology in robotics is continuously advancing, supported by developments in electronics and control systems. Consequently, robots are increasingly used to serve human needs. A critical component in the movement of a robot is the arm, which functions as the primary manipulator. However, existing methods are suboptimal for controlling robot arms, especially in object manipulation and real-time control. Therefore, this study developed a robotic arm system for a five-degree-of-freedom service robot using the type-2 fuzzy logic method, designed to perform tasks such as gripping and moving objects automatically. The type-2 fuzzy logic system takes two inputs: Y-coordinates of the bounding box for object detection and depth estimation, with the output being the movement of the robot arm. Simulation results indicate that type-2 fuzzy logic with a seven-membership function performed better than type-1 fuzzy logic, achieving a steady-state error of 0,1342. In real-time testing, the service robot arm, using type-2 fuzzy logic with a seven-membership configuration, gripped and moved an empty bottle in 45 s and the filled bottle in 48 s. The robot arm successfully executed a handshake with a human in real time within 30 s. These findings validate the effectiveness of the robot arm with type-2 fuzzy logic.*

Keywords

Five DOF, Fuzzy logic, Robot arm, Service robot, Type-2 fuzzy logic.

1. Introduction

The Industrial Revolution, spanning from 1.0 to 4.0, has significantly impacted humanity. A key aspect of these revolutions was the development and implementation of robotics technology, which has existed since Industrial Revolution 3.0 [1]. Robotics has continued to evolve, particularly with developments in electronics and control systems. Consequently, robots are increasingly used to satisfy human needs, including assisting healthcare professionals [2–4] and contributing to social and residential life [5]. Robots are machines capable of performing specific operations [6], such as communication and movement, transportation, and object relocation. Robots are essential for tasks that are challenging for humans, such as high-risk tasks and those requiring high accuracy, repetitive actions, and significant physical effort [7]. Robots operating in complex environments must move quickly and stably [8]. A critical component of the movement of a robot is related to the robotic arm, which serves as its controller. Generally, these arms can be programmed to have functions comparable to those of a human arm [9]. Robotic arms, classified as industrial robots (ISO 8373), are widely used in various industries [7], including welding, gripping, punching, and machine tool operations [10]. Robotic arms are essential for both industrial and service robots.

In human–robot interactions, robotic arms must learn human arm movements and integrate these patterns into their motion planning [11]. A robotic arm requires a control method that enables automatic operation and regulates the movement, lifting, and placing of objects. Robotic arm movements are also influenced by object and facial recognition capabilities. Several studies have focused on developing methods for robotic arms to grasp and manipulate objects. Abbood et al. proposed a method to distinguish objects based on their color and shape, using the hue-saturation-value (HSV) model and position coordinates of the robotic arm [12]. However, this method depends on camera system illumination and resolution. Ribeiro et al. designed a robotic system for picking tomatoes based on You Only Look Once (YOLO) v5 [13, 14] and vision-based object grasping for robotic manipulators [15]. However, most of these studies were limited to simulations and were implemented only on robotic manipulators.

Robotic arm controllers are crucial to ensure that the arm can move or grasp an object. Various studies have proposed control methods for robotic arms. Sultan and Jajes proposed a proportional-integral-derivative (PID) system using the Zeigler–Nichols method together with the bee colony algorithm to determine the optimal parameters [16]. However, this method was evaluated solely through robotic arm simulation. For flexible joints [17], a fuzzy-PID controller design for a four-degree-of-freedom (DOF) industrial robotic arm manipulator has been proposed [18]. Khatib and Maged proposed a fuzzy-PID controller to improve the response speed and minimize the overshoot of a robotic arm [19]. Other researchers also used PID control to increase the accuracy of robotic arm positioning [20, 21]. Meanwhile, Dewi et al. utilized a fuzzy logic controller for a robotic arm system; however, this system was only evaluated via simulations and not under real-time conditions [22]. Real-time object detection and robust control systems play a crucial role in the arms of service robots.

Therefore, this study aims to enhance the control performance of service robot arms. Instead of using conventional approaches, which rely only on a robot model and its parameters [16], this study utilizes computer-vision input from YOLO using images captured by the service robot.

In service robot applications, the number of DOFs influences the performance of the robotic arm. The number of DOFs refers to the number of joints in a human arm. In the context of robotic arms, DOFs determine the range of movements and tasks a robot can perform to perform various movements and functions. Five DOFs are commonly used in many applications because they provide sufficient flexibility for several general manipulation tasks, such as picking and placing objects in various positions and orientations.

In this study, a robotic arm system was developed for a five-DOF service robot using the type-2 fuzzy logic method, which was designed to automatically perform tasks such as grasping, lifting, and moving objects. Fuzzy logic was used in this study as a control method owing to its mathematical simplicity and ability to handle uncertainty in data, similar to human reasoning. The control system of the robotic arm uses the type-2 fuzzy logic method, which provides greater flexibility than the type-1 fuzzy logic method and enables the modeling of highly nonlinear systems essential for controlling a robotic arm with flexible joints. The inputs for this system included the object coordinates obtained from the YOLO algorithm, which recognized the objects, and the data from the distance sensor used to control the movement of the fingers of the service robot.

The contributions of this study are as follows:

- This study achieves real-time implementation of a five-DOF robotic arm capable of grasping and holding objects.
- The fuzzy logic control system utilizes visual input from a deep-learning-based convolutional neural network and includes the position, distance, and type of the object.
- The proposed control system employs type-2 fuzzy logic, and it can achieve smoother robotic arm movements than type-1 fuzzy logic.

The remainder of this paper is structured as follows. Section 2 describes the methods used in this study. Section 3 presents the results and discussion, and Section 4 concludes the paper.

2. Methods

2.1. Design of the Service Robot

The service robot arm was designed using SolidWorks software and fabricated using three-dimensional (3D) printing with filament-based material. The shoulders of the robot arm are equipped with two direct current (DC) worm gear motors. The first DOF of the service robot arm lifts the service robot arm. The second DOF is used to move the arm up or down and expand the shoulder. The third DOF functions as the wrist, enabling hand rotation, whereas the fourth DOF acts as the elbow, enabling the arm to lift. Finally, the fifth DOF controls the fingers of the robot. The 3D design is shown in Fig. 1.

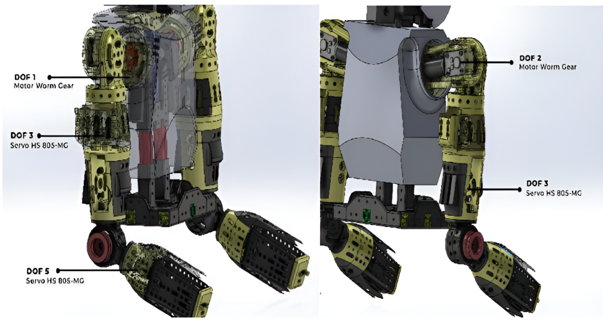


Fig. 1: Design of the service robot arm.

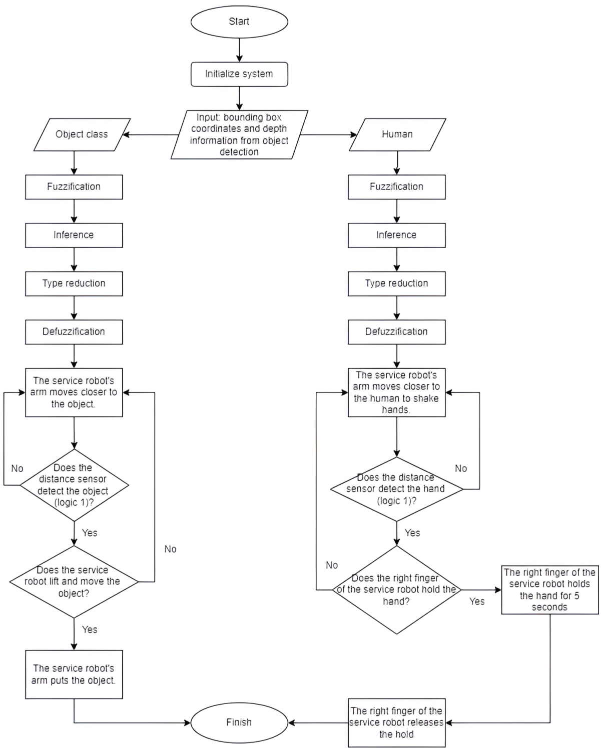


Fig. 2: Working system of the robot arm.

2.2. Control Steering System

The robot arm system initializes components, such as the microcontroller, servos, and sensors. Next, the system reads the inputs, such as the coordinate outputs from YOLO, depth information, and input class readings. If the input indicates an object class and/or a human, it proceeds to the next stage: fuzzification, inference, type reduction, and defuzzification. After fuzzification, the robot arm approaches the object. For object classes, if the distance sensor detects logic 1, the fingers of the robot grip the object, and the process is complete. However, if the proximity sensor detects logic 0, the robotic arm continues to approach the object. For the human class, if the distance sensor detects logic 1, then the fingers of the robot grip the human's hand. Conversely, if the distance sensor still detects logic 0, then the robot arm continues to approach the object. The system workflow of the robot arm is shown in the flowchart in Fig. 2.

2.3. Type-2 Fuzzy Logic

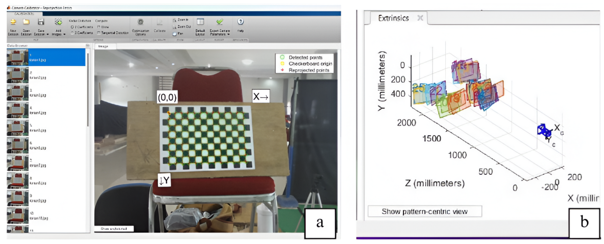


Fig. 3: Coordinate system of the camera.

Two main input variables were used in this study: Y-coordinates from the YOLO v8 algorithm [23] and the object distance (depth estimation) [24]. The coordinate system of the camera can be seen in Fig 3. The distance from the object requires the use of the camera's geometric parameters to accurately calculate the distance. For the camera calibration process, the checkerboard method is used to obtain the intrinsic parameters of the camera. After the calibration process is completed, focal lengths of 722.0217 and 722.9921 for the x- and y-axes are obtained, respectively. Objects and faces are measured using the focal lengths obtained after the camera has been calibrated, along with parameters from the resulting bounding box frame. Each bounding box frame displays four variables used in distance measurements: (x1, y1, x2, y2). Here, x1 and y1 represent the x- and y-coordinates of the top-left corner of the bounding box, while x2 and y2 represent the x- and y-coordinates of the bottom-right corner of the bounding box. These coordinates are then further processed to obtain the width and height values of each bounding box as

$$width = (x2 - x1) \tag{1}$$

$$height = (y2 - y1) \tag{2}$$

The object distance can then be calculated via monocular distance estimation as follows:

$$distance = \frac{\text{actual height} \times \text{focal length } y}{\text{bounding box height}} \tag{3}$$

These two inputs were integrated into a type-2 fuzzy logic system to manage uncertainty and variability in the input data. The YOLO Y-coordinates were classified into seven sets: very left, left, slightly left, center, slightly right, right, and very right. Figure 4 shows the input variable chart for YOLO with seven memberships, where the YOLO variable values for 7, 5, and 3 memberships range from 0–640. These values are based on the width and length obtained by YOLOv8.

The distance (depth estimation) variable had seven-membership categories: very close, close, somewhat close, medium, quite far, far, and very far. The input variable chart for the distance with seven memberships is shown in Fig. 5, and the values of the distance (depth estimation) variable ranged from 30–55. The membership functions for the input are listed in Tabs. 1 and 2. Meanwhile, the membership functions for the output of the right and left service robot arms are shown in Tabs. 3 and 4, respectively.

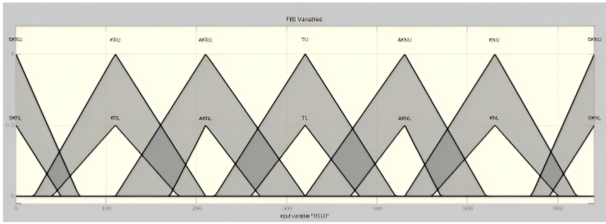


Fig. 4: Input variable with seven memberships from YOLO.

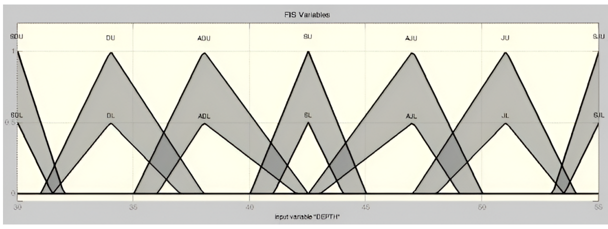


Fig. 5: Input variable with seven memberships from the distance (depth information).

In this study, two input variables with seven-membership functions were considered, resulting in 49 rules, and these rules are summarized in Tab. 5. Furthermore, the rule-based systems for three and five membership functions have 9 and 25 rules, respectively, as presented in Tab. 7 and 6.

3. Results and Discussion

3.1. Simulation

The simulation testing process started with the development of a type-2 fuzzy logic model in Simulink, which included defining the membership functions for both the input and output, as well as the fuzzy inference rules. System inputs, including YOLO coordinates and distance (depth estimation), were inputted into the model to simulate real-world scenarios. The schematic of the model simulated in Simulink is shown in Fig. 6.

In this simulation, only one DC servo motor is used to represent the movement of a degree of freedom (DOF), as all DOFs are driven by DC servo motors. The equation of the DC motor, considered as the plant, is shown below:

$$G_v(s) = \frac{\dot{\theta}(s)}{V_a(s)} = \frac{K_T}{(R_a + sL_a)(sJ + B_0) + K_T K_b} \tag{4}$$

where K_T is the torque constant, and the other parameters include the armature resistance (R_a), armature inductance (L_a), armature voltage (Ea), back EMF constant (K_b), moment of inertia (J), and viscous friction coefficients (B_0). This model represents a DC servo motor, which serves as the main component for the movement of the robotic arm. Table 8 lists the DC servo motor parameters used in this study, representing the movement of the DOF in the robotic arm. In this simulation, the rotational speed was the output variable as we aimed to analyze the performance of Type-1 and Type-2 fuzzy logic controllers in terms of system response. Moreover, the speed was determined by taking the first derivative of the position, which corresponds to the input coordinates and depth information, using a setpoint of 100.

Using the parameters presented in Tab. 8, the following can be obtained:
$G_v(s) = \frac{\dot{\theta}(s)}{V_a(s)} = \frac{0.806}{0.000026s^2+0.005104s+0.666412}$

This simulation test used Type-1 and Type-2 fuzzy logic controllers—each configured with three-, five-, and seven-membership function configurations, as well as a PID controller. Tests were conducted to analyze the system response when a set point of 100 was applied. The analysis focused on how quickly and accurately the system achieved the desired output. A comparison of the overall simulation results using three-, five-, and seven-membership function configurations for both Type-1 and Type-2 fuzzy logic controllers, as well as the PID controller, is presented in Fig. 7.

Figure 6 indicates that the type-2 fuzzy logic model outperforms the type-1 fuzzy logic model. This result suggests that the real-time implementation of robotic arm control using type-2 fuzzy logic can produce a more stable response. The response results of types-1 and -2 fuzzy logic models are presented in Tab. 9 and 10, respectively.

As shown in Tab. 9 and 10, Type-2 fuzzy logic demonstrates a lower steady-state error compared to Type-1 fuzzy logic. Specifically, Type-2 fuzzy logic with seven-membership functions exhibits a faster rise time (0.3519 s) than the Type-1 system (0.4756 s). Moreover, the settling time for the Type-2 system is significantly shorter (2.3172 s) than that of Type-1 (4.2128 s), and Type-2 fuzzy logic attains steady state more rapidly with a steady-state error of 0.1342, which is markedly lower than that observed in Type-1 fuzzy logic (1.6130). Across all membership function configurations, Type-2 consistently achieves a lower steady-state error than Type-1.

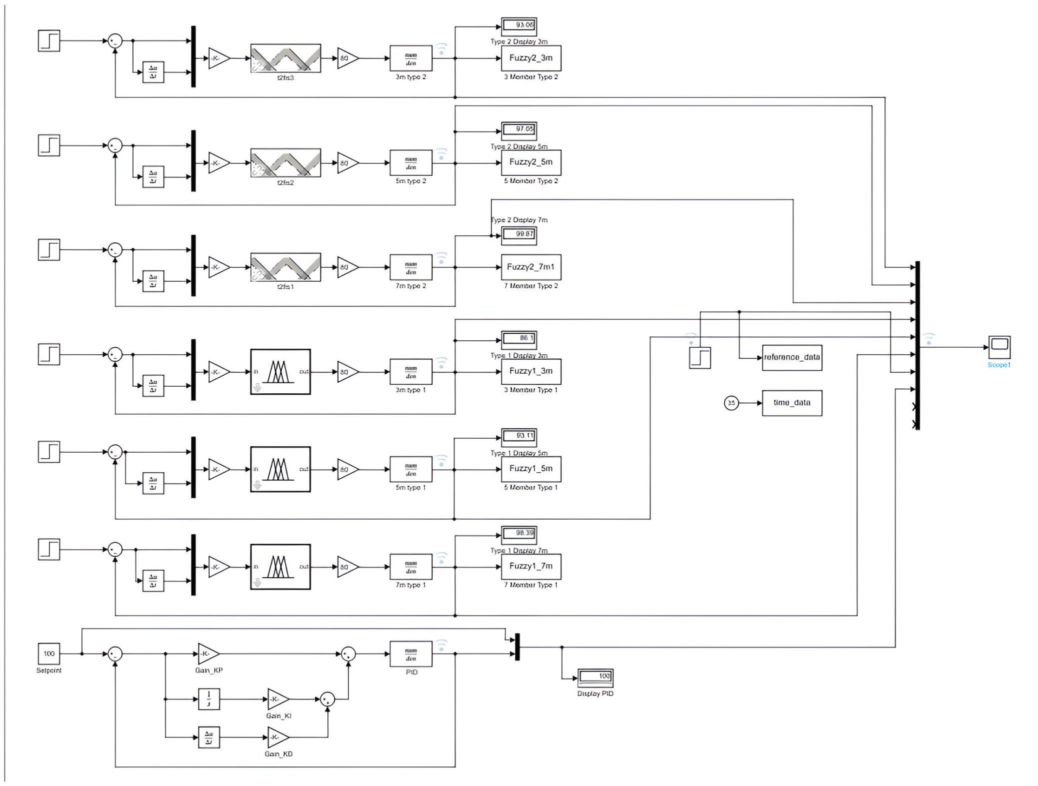


Fig. 6: Schematic of the type-2 fuzzy logic model simulated using Simulink.

Tab. 1: Membership function for the input bounding box y-coordinates.

Interval	7-member	5-member	3-member	Membership function
Upper	0–70	0–160	-	Very Left (SKR)
Lower	0–50	0–90	-	
Upper	20–210	20–320	0–320	Left (KR)
Lower	40–180	70–250	0–220	
Upper	110–320	-	-	Slightly left (AKR)
Lower	170–270	-	-	
Upper	220–420	170–470	120–520	Middle (T)
Lower	260–380	230–410	140–500	
Upper	320–520	-	-	Slightly right (AKN)
Lower	370–470	-	-	
Upper	430–620	320–620	320–640	Right (KN)
Lower	460–600	390–570	420–640	
Upper	570–640	480–640	-	Very right (SKN)
Lower	590–640	550–640	-	

In addition, a comparison between the Type-2 fuzzy logic controller (FLC) and PID controller (Tab. 11) indicates that the Type-2 FLC achieves a faster rise time (0.3519 s) compared to PID (0.4310 s). This suggests that the Type-2 FLC requires less time to rise from 10% to 90% of its steady-state value. Moreover, the steady-state error of the Type-2 FLC is lower than that of the PID controller (0.1892), indicating a more accurate system response under steady-state conditions. Nevertheless, it should be noted that the Type-2 fuzzy logic controller tends to exhibit a higher overshoot compared to PID. This behavior is attributed to the greater number of rules and the increased complexity of the membership functions in the Type-2 FLC, which can lead to a more aggressive response to input variations.

Considering the above results, the Type-2 fuzzy logic controller is used for real-time implementation. As the rotational speed is determined via the first derivative of the position, simulation-based verification is sufficient to assess the robustness of the Type-2 fuzzy controller. As shown in Fig. 7, although the PID controller may achieve a lower overshoot than the Type-2

Tab. 2: Membership function for input depth information.

Interval	7-member (cm)	5-member (cm)	3-member (cm)	Membership function
Upper	30–32	30–34.7	-	Very near (SD)
Lower	30–31.5	30–34	-	
Upper	31–38	31.5–42.5	30–42.5	Near (D)
Lower	31.5–37	32.2–40	30–37.82	
Upper	35–42	-	-	Rather near (AD)
Lower	36–42	-	-	
Upper	40–45	37.8–47.2	34.69–50.32	Currently (S)
Lower	41–44	39.3–45.6	36.25–48.75	
Upper	42.5–50	-	-	Rather far (AJ)
Lower	43–49	-	-	
Upper	47–54	42.5–53.4	42.5–55	Far (J)
Lower	48–53.5	45–52.8	47.19–55	
Upper	53–55	50.3–55	-	Very far (SJ)
Lower	53.5–55	51–55	-	

Tab. 3: Membership functions for the output of the right service robot arm.

Variable	DOF 1	DOF 2	DOF 3	DOF 4	DOF 5
Left-Proceed	710	760	150	55	60
Left	700	760	150	50	60
Middle	680	760	130	40	70
Middle Proceed	700	760	130	55	70
Right	670	750	115	40	80
Right Proceed	690	750	115	55	80

Tab. 4: Membership function for the output of the left service robot arm.

Variable	DOF 1	DOF 2	DOF 3	DOF 4	DOF 5
Left-Proceed	450	580	70	140	95
Left	460	580	80	150	90
Middle	460	560	65	140	95
Middle Proceed	450	560	55	130	100
Right	440	540	35	140	120
Right Proceed	420	540	40	130	120

fuzzy controller, it requires a longer duration to reach steady-state. This characteristic is critical in applications such as controlling the speed of a DC servo motor during gripping and grasping tasks in robotic arms. Therefore, the Type-2 fuzzy logic controller offers significant advantages for integration into the arm of a service robot.

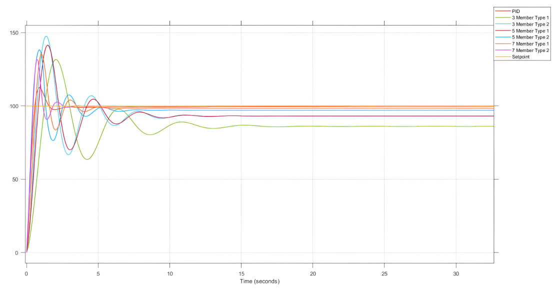


Fig. 7: Comparison of Type-1 and Type-2 fuzzy logic controllers with three-, five-, and seven-membership functions, as well as a PID controller.

3.2. Real-Time Test

The real-time testing of the robotic arm was conducted using the type-2 fuzzy logic system with seven-, five-, and three-member configurations. Testing with three- and five-member configurations was limited to bottle handling and handshaking. Other objects were excluded as the performance of type-2 fuzzy logic control with three- and five-member configurations was deemed sufficient to represent the performance.

Figure 8 shows the handshake test results. Table 12 shows that the seven-member robotic arm achieved an accuracy of 69.23% in the handshake test, with nine successful attempts out of 13 tests and an average success time of 32.11 s. However, four of 13 tests were unsuccessful, primarily because multiple hand readings/detections were unreadable by the camera. In contrast, the robotic arm with the five- and three-member configurations, as shown in Tab. 13 and 14, achieved a success rate of 40% in the handshake test, with two successful attempts out of five tests for each configuration (each configuration was tested five times) and an average success time of 30.5 s for the five-member configuration and 32.5 s for the three-member

Tab. 5: Rules of seven members.

Rules	Inputs Fuzzy		Fuzzy Outputs
	Coordinate YOLO	**Depth Estimation**	
1	Very Left	Very Near	Out Left
2	Very Left	Near	Out Left
3	Very Left	Rather Near	Out Left
4	Very Left	Currently	Out Left
5	Very Left	Rather Far	Out Left
6	Very Left	Far	Out Left Proceed
7	Very Left	Very far	Out Left Proceed
8	Left	Very Near	Out Left
9	Left	Near	Out Left
10	Left	Rather Near	Out Left
11	Left	Currently	Out Left
12	Left	Rather Far	Out Left Proceed
13	Left	Far	Out Left Proceed
14	Left	Very far	Out Left Proceed
15	Slightly left	Very Near	Out Left
16	Slightly left	Near	Out Left
17	Slightly left	Rather Near	Out Left
18	Slightly left	Currently	Out Left Proceed
19	Slightly left	Rather Far	Out Left Proceed
20	Slightly left	Far	Out Left Proceed
21	Slightly left	Very far	Out Left Proceed
22	Middle	Very Near	Out Middle
23	Middle	Near	Out Middle
24	Middle	Rather Near	Out Middle
25	Middle	Currently	Out Middle
26	Middle	Rather Far	Out Middle Proceed
27	Middle	Far	Out Middle Proceed
28	Middle	Very far	Out Middle Proceed
29	Slightly right	Very Near	Out Right
30	Slightly right	Near	Out Right
31	Slightly right	Rather Near	Out Right
32	Slightly right	Currently	Out Right Proceed
33	Slightly right	Rather Far	Out Right Proceed
34	Slightly right	Far	Out Right Proceed
35	Slightly right	Very far	Out Right Proceed
36	Right	Very Near	Out Right
37	Right	Near	Out Right
38	Right	Rather Near	Out Right
39	Right	Currently	Out Right
40	Right	Rather Far	Out Right Proceed
41	Right	Far	Out Right Proceed
42	Right	Very far	Out Right Proceed
43	Very right	Very Near	Out Right
44	Very right	Near	Out Right
45	Very right	Rather Near	Out Right
46	Very right	Currently	Out Right
47	Very right	Rather Far	Out Right Proceed
48	Very right	Far	Out Right Proceed
49	Very right	Very far	Out Right Proceed

Tab. 6: Rules of five members.

Rules	Inputs Fuzzy		Fuzzy Outputs
	Coordinate YOLO	Depth Estimation	
1	Very Left	Very Near	Out Left
2	Very Left	Near	Out Left
3	Very Left	Currently	Out Left
4	Very Left	Far	Out Left Proceed
5	Very Left	Very Far	Out Left Proceed
6	Left	Very Near	Out Left
7	Left	Near	Out Left
8	Left	Currently	Out Left Proceed
9	Left	Far	Out Left Proceed
10	Left	Very Far	Out Left Proceed
11	Middle	Very Near	Out Middle
12	Middle	Near	Out Middle
13	Middle	Currently	Out Middle
14	Middle	Far	Out Middle Proceed
15	Middle	Very Far	Out Middle Proceed
16	Right	Very Near	Out Right
17	Right	Near	Out Right
18	Right	Currently	Out Right Proceed
19	Right	Far	Out Right Proceed
20	Right	Very Far	Out Right Proceed
21	Very Right	Very Near	Out Right
22	Very Right	Near	Out Right
23	Very Right	Currently	Out Right
24	Very Right	Far	Out Right Proceed
25	Very Right	Very Far	Out Right Proceed

Tab. 7: Rules of three members.

Rules	Inputs Fuzzy		Fuzzy Outputs
	Coordinate YOLO	Depth Estimation	
1	Left	Near	Out Left
2	Left	Currently	Out Left
3	Left	Far	Out Left Proceed
4	Middle	Near	Out Middle
5	Middle	Currently	Out Middle
6	Middle	Far	Out Middle Proceed
7	Right	Near	Out Right
8	Right	Currently	Out Right
9	Right	Far	Out Right Proceed

Tab. 8: Parameters of the DC Servo Motor.

Parameter	Value
K_T	$0.806\, Nm/A$
R_a	$2\,\Omega$
L_a	$0.5\, H$
E_a	$6\, V$
K_b	$0.802\, V.s/rad$
J	$0.000052\, kg.m^2$
B_0	$0.01\, Nm.s/rad$

configuration. A type-2 fuzzy logic system with seven members has a higher computational capacity, enabling it to accommodate various operating conditions compared to systems with five members or fewer. This increased computational capacity improves output accuracy in response to input changes.

The standard deviation of the time required in the handshake tests is shown in Fig. 9. The standard deviation of the handshake test with the seven-member configuration (5.0606) is slightly greater than those of the five-member (2.4166) and three-member (4.5343)

Tab. 9: Type-1 fuzzy logic.

No.	Parameter	Type 1 Fuzzy Logic		
		Three Members	Five Members	Seven Members
1	Rise Time	0.7954 s	0.5771 s	0.4756 s
2	Settling Time	11.5333 s	8.3385 s	4.2128 s
3	Peak Time	2.0 s	1.5 s	1 s
4	Overshoot	52.8187%	51.9538%	37.7778%
5	Steady-State Error	13.9023	6.8874	1.6130

Tab. 10: Type-2 fuzzy logic.

No.	Parameter	Type-2 Fuzzy Logic		
		Three Members	Five Members	Seven Members
1	Rise Time	0.4977 s	0.3239 s	0.3519 s
2	Settling Time	8.3111 s	5.4025 s	2.3172 s
3	Peak Time	1.4 s	0.9 s	0.7 s
4	Overshoot	58.6791%	42.6695%	32.1556%
5	Steady-State Error	6.9407	2.9502	0.1342

Tab. 11: PID controller.

No	Parameter	PID
1	Rise Time	0.4310 s
2	Settling Time	2.1863 s
3	Peak Time	0.9 s
4	Overshoot	12.8110
5	Steady-State Error	0.1892

Fig. 8: Handshake test.

configurations. This occurred because the number of trials in the seven-member configuration is greater than those in the three- and five-member configurations. In addition, the number of successful handshakes in the seven-member configuration is greater than in the other configurations.

Figures 10 and 11 illustrate the angular changes for each DOF of the service robot arm. The robot remains on standby from 1 to 6 s before initiating movement from 7 to 27 s. The robot takes 20 s to complete its task. After completing the handshake, the robot arm returns to standby from 28 to 34 s.

Figure 12 illustrates that the Thumb-up variable first moves at 11 s, reaching an angle of 800, followed by the other fingers at 12 s with an angle change toward 140. The servo conducts the handshake from 14 to 21 s and from 22 to 25 s, completing the motion, and all servos return to standby. The DOF and finger movements follow similar patterns for all other tasks, such as moving an empty cup and moving filled bottles.

The comparison of the seven-, five-, and three-member systems using type-2 fuzzy logic for different tasks is shown in Tab. 15. The seven-member robotic arm achieved an accuracy of 60% in the empty bottle holding test, with nine successful attempts out of 15 tests and an average time of 45.8 s. Empty bottles are susceptible to touch and would often fall during attempts to approach them. Nevertheless, sufficiently successful results were achieved because the fingers of the robot could effectively grasp and move the object.

The seven-member robotic arm achieved an accuracy of 53.3% in the filled bottle holding test, with eight successful attempts out of 15 tests and an average time of 41.62 s. In several tests, the grippers did not effectively grasp the object, causing it to move regardless of the grip strength of the fingers of the robot. This was also attributed to the object being relatively heavier than others. In contrast, the robotic arm with five-member and three-member configurations demonstrated an inferior accuracy in this test, specifically 0%, with no successful attempts in 10 tests (each configuration was tested five times).

Tab. 12: Handshake — seven-member configuration.

No.	Fuzzy Input YOLO		Time (s)	Remarks
	YOLO	Depth		
1	117	52	40	Successful
2	153	51	29	Successful
3	147	52	27	Successful
4	160	54	28	Successful
5	430	41	28	Unsuccessful
6	443	43	30	Successful
7	386	41	34	Successful
8	213	52	32	Unsuccessful
9	310	53	31	Successful
10	315	54	36	Unsuccessful
11	409	42	30	Successful
12	317	50	40	Successful
13	267	49	43	Unsuccessful

Tab. 13: Handshake — five-member configuration.

No.	Input Fuzzy		Time (s)	Remarks
	YOLO	Depth		
1	305	49	35	Unsuccessful
2	107	50	33	Successful
3	121	48	28	Successful
4	289	49	34	Unsuccessful
5	292	48	32	Unsuccessful

Tab. 14: Handshake — three-member configuration.

No.	Fuzzy Input		Time (s)	Remarks
	YOLO	Depth		
1	142	52	35	Successful
2	176	48	30	Successful
3	196	46	30	Unsuccessful
4	268	53	30	Unsuccessful
5	289	53	21	Unsuccessful

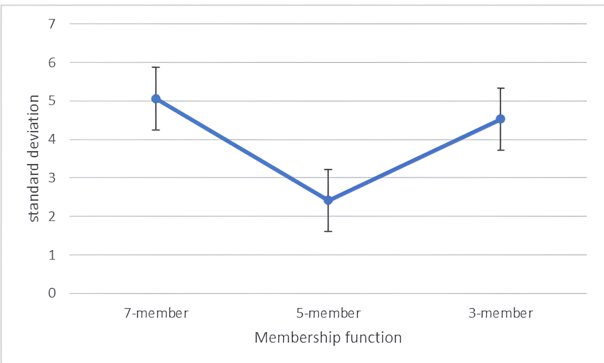


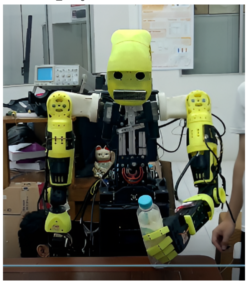
Fig. 9: Standard deviations of the handshake tests.

The seven-member robotic arm achieved an accuracy of 53.3% in the empty cup moving test, with eight successful attempts out of 15 tests and an average time of 40.12 s. In several tests, the attempts of the robotic arm to approach the cup displaced it, causing it to move backward. The slippery surface of the cup affected the grip, which in turn affected the accuracy of the results.

The seven-member robotic arm achieved a success rate of 58.3% in the filled cup moving test, with seven successful attempts out of 12 tests and an average time of 46.4 s. The success rate of grasping the filled cup was the same as that of grasping the empty cup, with seven successful attempts. During these tests, when the robotic arm attempted to approach the object, it slightly pushed the cup. However, the cup did not move backward because the weight of the water inside the cup likely influenced its position.

The robotic arm with the five-member and three-member configurations achieved a 0% success rate in the filled bottle holding test. This was attributed to several factors, including the limited number of mem-

Tab. 15: Comparison of the configurations (7, 5, and 3) of the Type-2 fuzzy logic model.

Objects/Things	Membership	Level of Success (%)	Average Time of Success (s)
Empty Cup Test 	Seven members	53.3	40.12
Filled Cup Test 	Seven members	58.3	46.4
Empty Bottle Test 	Seven members	60	45.8
Filled Bottle Test 	Seven members	53.3	41.62
	Five members	0	-
	Three members	0	-
Handshake Test 	Seven members	69.23	32.11
	Five members	40	30.5
	Three members	40	32.5

bership functions used. With fewer membership functions, the system could not capture the changes in input variables effectively, resulting in less precise outputs compared with a system with more membership functions. Consequently, systems with five- and three-member configurations produced responses that were

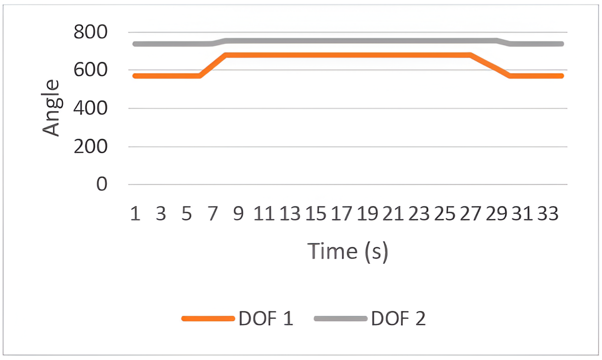


Fig. 10: Graphs of DOF-1 and DOF-2 during the handshake test with seven members.

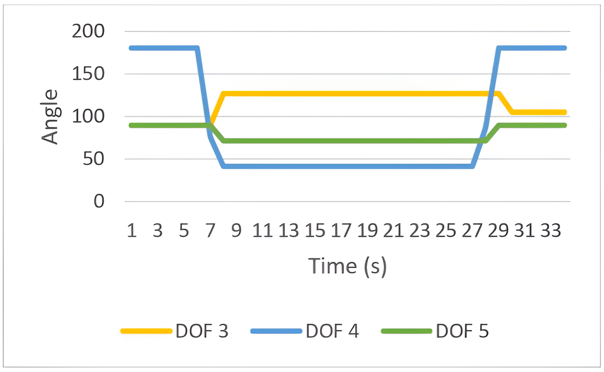


Fig. 11: Graphs of DOF-3, DOF-4, and DOF-5 during the handshake test with seven members.

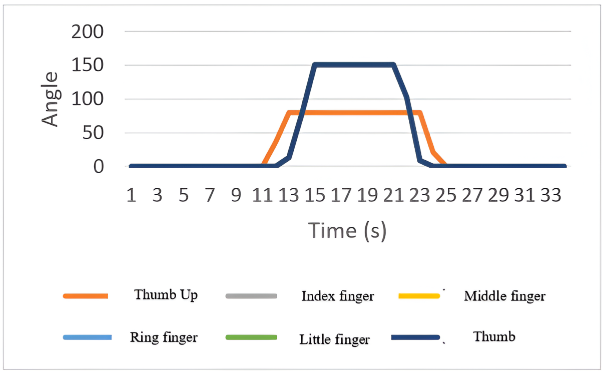


Fig. 12: Angle of the fingers during the handshake test with seven members.

too rough to handle small changes in the input, leading to inaccurate outputs.

The results in Tab. 15 indicate that the success rate of the robotic arm in grasping objects depends on the shape of the object. A bottle, which has a rounded shape, was easier to grasp compared to a cup or a hand. Additionally, the weight of the object influences the ability of the robot to hold it. For example, a higher success rate was achieved for the cup filled with water than for the empty cup, which may be because the cup filled with water is more stable than the empty one. Moreover, the time needed by the robotic arm to successfully perform a handshake was faster than the time needed to grasp the cup or bottle. This suggests that the bottle and cup have more complex shapes compared to the hand.

4. Conclusion

This study demonstrated that type-2 fuzzy logic can effectively control a five-DOF service robot arm. This study utilized two input types: the Y-coordinates from the object detection results and the depth estimation, both derived from object detection. The resulting output was the movement of each DOF in the robotic arm. Results indicate that the type-2 fuzzy logic model with the seven-member configuration outperformed the type-1 fuzzy logic model, as noted in the steady-state error value from the simulations using MATLAB Simulink, as shown by a steady-state error of 0.1342.

Real-time testing involved empty and filled bottles and cups. Tests using the seven-member type-2 fuzzy logic system showed that the robotic arm achieved success rates of 53%, 58.3%, 60%, and 53.3% in the empty cup, filled cup, empty bottle, and filled bottle tests, respectively. Additionally, the robot successfully performed handshakes in real time, achieving a 69.23% success rate with an average time of 32.11 s. Therefore, the implemented system accurately detected, identified, and interacted with objects. However, failures persisted owing to inaccuracies in object detection readings. Future work will focus on improving object detection methods to improve the accuracy of the service robot in detecting and recognizing objects. Nonetheless, results demonstrate that the five-DOF service robot with fuzzy logic type-2 can be implemented for real-time arm operation using information from deep learning.

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Author Contributions

S. D. and A. A. conceived and planned the experiments. S.D. performed conceptualization, methodology, formal analysis, and writing – original draft preparation. B. Y. S. performed writing – review and editing. S. D. and B. Y. S. supervised the project. A. A. carried out the experiments and performed investigation. H. H. and I. I. contributed to the final version of the manuscript.

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