Journal of Robotics and Control (JRC)
Volume 5, Issue 6, 2024
ISSN: 2715-5072, DOI: 10.18196/jrc.v5i6.23579

Combining Finite State Machine and Fuzzy Logic Control for Accuracy Enhancing Performance of a Tomato-Handling Robot Gripper

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***Abstract*—Robotic grippers are becoming increasingly vital in modern agriculture, especially in tasks like harvesting delicate crops such as tomatoes, where precision and care are crucial. These advanced tools are designed to handle tomatoes without causing damage, significantly improving efficiency and reducing labor costs. Research on gripper robots for fruit picking continues to be developed using various methods in an effort to achieve accurate picking results. This study proposes a hybrid method that combines Finite State Machine (FSM) for behavior control with Fuzzy Logic Control (FLC) to optimize the positioning of the gripper. The system utilizes a PixyCam2 CMUcam5 for tomato detection, an Arduino microcontroller for image processing, and a servo mechanism to precisely align the gripper with the target. The experimental results confirm that each component functions as expected, with the gripper successfully performing actions such as idling, gripping, and placing in accordance with the FSM model.Furthermore, the FLC model was tested against simulations, resulting in error rates of 1.004% for the elbow angle and 0.826% for the base angle. The entire system was validated by comparing the performance of the system using FLC and non-FLC in ten tests, each with tomatoes placed in different positions. The results indicate that the proposed gripper, utilizing the FSM-FLC model, achieved a 100% success rate in grasping the target, significantly outperforming the FSM-non-FLC gripper, which achieved only a 20% success rate. These findings have important implications for the agricultural industry. The successful integration of the FSM and FLC models in robotic grippers paves the way for fully automated harvesting systems, potentially reducing costs and enhancing productivity.**

Keywords*—Finite State Machine; Fuzzy Logic Control; Robotic Gripper; Tomato Harvesting, Agricultural Robotic.

I. INTRODUCTION

The agricultural sector has recently witnessed a surge in technological advancements aimed at enhancing efficiency and productivity. Among these innovations, robotic grippers designed specifically for agricultural applications have garnered significant attention. These robots play a crucial role in tasks such as harvesting and handling delicate produce, offering the precision and dexterity necessary for such operations [1]. Modeled to replicate the sensitivity and precision of human hands, these grippers gently interact with crops while maintaining operational efficiency [2]. For instance, a study focused on developing a robotic gripper for tomato harvesting emphasizes the need to consider factors such as the growing environment, fruit size, and human physiological characteristics related to grasping [3]. Additionally, the complexity of grasping agricultural products, which necessitates the use of various sensors to enhance flexibility and control, surpasses the requirements of industrial applications [4]–[10].

Robotic grippers play a critical role across various sectors, including agriculture, manufacturing, and healthcare, due to their capacity for precise object manipulation [11]–[15]. Recent advancements, such as reconfigurable finger bases and selectively lockable joints, have enhanced the dexterity of these systems while maintaining operational efficiency [16]. The effectiveness of object manipulation relies heavily on the coordination between gripper control and manipulator movement [17], [18]. Furthermore, the integration of advanced real-time systems, which predict object motion and dynamically adjust control commands, has significantly enhanced the overall performance of robotic systems in tasks such as object picking and placing [19].

The integration of bioimpedance sensors and artificial intelligence (AI) has further revolutionized the functionality of robotic grippers in agriculture. AI-driven robotic systems equipped with vision-based sensors, path manipulators, and end-effectors have improved precision in tasks such as seedling pickup and soil analysis, contributing to more sustainable farming practices [20]. Soft robotic grippers, utilizing advanced materials like anisotropic composites, offer adaptability and gentle handling of diverse crops, ensuring efficient grasping with minimal damage [21], [22].

To execute complex tasks, robotic grippers require multiple local controllers working in unison [23]. A meta-control mechanism, such as a finite state machine (FSM), is necessary for switching between controllers [24]. FSMs are widely employed in modeling and controlling robotic systems, including robot grippers, to govern behavior and decision-making processes based on predefined states and transitions [25]–[29]. In robotic grippers, FSMs provide a structured approach for managing actions, allowing grippers to adapt to various scenarios and perform specific tasks efficiently [30], [31]. The FSM framework defines the gripper's states, the conditions for transitioning between these states, and the corresponding actions, ensuring a clear, organized method for controlling the gripper's operations.

Recent advancements in 3D perception and manipulation technologies have further enhanced the role of robotic grippers in agricultural tasks such as tomato harvesting. The integration of end-effectors, 3D perception systems, and precise cutting mechanisms has improved both the efficiency and accuracy of robotic harvesting [32]. FSMs, through their structured control and behavior mechanisms, continue to play a vital role in enabling grippers to adapt to different tasks and scenarios [30], [31].

Fuzzy Logic Control (FLC) has emerged as a crucial tool for improving robotic systems by handling uncertainties and imprecise data, thus enabling more accurate decision-making [33]. In robotic grippers, FLC is integrated with impedance and iterative learning methods to enhance grasping performance [34]. This approach demonstrates the flexibility of fuzzy logic, providing an adaptable control mechanism for a variety of robotic tasks.

The application of FLC in robotics extends beyond simple control tasks. It has been widely implemented in fields such as regulation [35]–[37], the motion control of robot [38], [39], monitoring [40], decision-making [41]–[43], and accuracy enhancement [44]. Research has shown that fuzzy controllers enable robots to navigate complex and dynamic environments while avoiding obstacles [45]–[51]. In particular, fuzzy logic has significantly enhanced the trajectory tracking control of manipulators like tendon-driven truss-like manipulators, utilizing advanced fuzzy logic methodologies [52].

In robotic grippers, the implementation of FLC has proven valuable, particularly when combined with other control architectures such as impedance and iterative learning methods. This combined approach enhances the grasping capabilities of robotic grippers by providing adaptive and flexible control mechanisms [34], [53]. The integration of fuzzy logic within robotic systems showcases its versatility in improving performance and decision-making processes, even in uncertain and complex environments [33].

In the other side, robotic grippers continue to evolve through the integration of advanced control strategies, sensing modalities, and material sciences. In this study, a robotic gripper is developed using digital image recognition to detect objects. Prior research has applied multiple techniques, such as Convolutional Neural Networks [54], muscle electrical signals [55], reinforcement learning [56], and hybrid brain-machine interfaces [57], to model robotic arm movement. This study adopts a combination of finite state machine and fuzzy logic control to calculate the arm's angles, ensuring accuracy during object picking.

In conclusion, robotic grippers are continuously evolving through the integration of advanced technologies and design principles, significantly enhancing their manipulation capabilities across various industries. By incorporating control strategies, sensing technologies, and innovations in material science, robotic grippers are becoming increasingly adept at performing precise and efficient manipulation tasks. Previous research has explored the development of robotic grippers using methods such as Convolutional Neural Networks (CNN) [54], Muscle Electrical Signals [55], Reinforcement Learning [56], Hybrid Gaze–Brain Machine Interfaces [57], and Fuzzy Logic Control (FLC) [58]. However, there remains limited research on hybrid approaches that combine multiple methods for gripper robots. The novelty of this study lies in combining two methods, namely Finite State Machine (FSM) and FLC, to optimize the gripper's performance in tomato-picking tasks.

This paper is organized into four sections. The first section provides an introduction. Section two details the methods, including FSM and fuzzy control, for developing the robotic gripper for tomato picking. Section three presents and discusses the results. Finally, section four concludes by summarizing the findings on the implementation of the FSM-FLC hybrid approach in robotic gripper systems for tomato-picking applications.

II. Method

The design process of our proposed robotic gripper consists of four main stages: robot design, development of the FSM model, development of the FLC model, and implementation. These stages will be further elaborated upon in this section. The flow process of our system is illustrated in Fig. 1. Based on Fig. 1, the system consists of three main stages: input, process, and output. In this system, the input is the target position (x, y), which is captured by the Pixy2 CMUCam5 camera. The Pixy2 CMUCam5 detects the target by recognizing its color, with the target in this case being identified by its red hue. Furthermore, the target position will be sent to the Arduino microcontroller, where it will be processed using the FSM and FLC models. The system's output from this process will be the elbow angle and the base angle. Illustrations of these angles can be seen in Fig. 5 and Fig. 6. These angles will be used to control the servo motors, enabling them to perform the primary task of grasping the tomatoes. Next, the angle output is transmitted to the servos to carry out the tomato harvesting process. After harvesting, the robot gripper places the tomatoes into a designated basket.

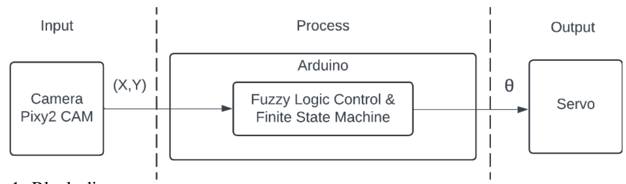
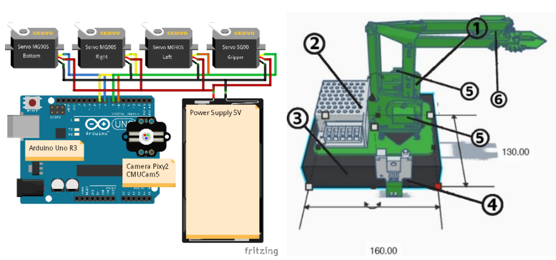


Fig. 1. Block diagram system.

The design of our proposed system is illustrated in Fig. 2, showcasing both 2D and 3D concepts. As depicted in Fig. 2, the proposed system consists of six main components. The main components of the system include a robotic arm, a 5V power supply unit (PSU) for power, an Arduino enclosure measuring 130 mm x 160 mm, a Pixy2 CMUCam5 for target detection, a servo motor for moving the robotic arm to capture the target, and a gripper servo for grasping the tomatoes. The selection of the Pixy2 CMUCam5 as the target-tracking camera is based on its integrated artificial intelligence capabilities, which make it highly efficient in color-based image capture. The Arduino microcontroller was chosen due to its compatibility with the Pixy2 CMUCam5 camera.



(a) (b)

Fig. 2. Design of robot gripper: (a) schematic design; (b) 3D design.

In this study, we employ a hybrid model that integrates a Finite State Machine (FSM) and Fuzzy Logic Control (FLC) to regulate the movement behavior of the robotic gripper. The FSM model consists of a set of states and transitions between state pairs [59]–[61]. Each transition is labeled with a condition/action pair: the condition triggers the transition, while the action is executed when the transition occurs [62]–[65].

In this study, the Finite State Machine (FSM) model is employed to manage the robot's behavior by defining specific states and corresponding actions. The system transitions between states based on the occurrence of actions. Therefore, the first step in FSM modeling involves identifying the relevant states and actions. An illustration of these states and actions is presented in Fig. 3. As shown in Fig. 3, our FSM model consists of three states and six actions. The relationships between these states are explained in detail below.

1) **Idle**: The state refers to the phase in which the robot actively searches for the target object to be detected. Upon successfully identifying the object, the robot transitions to the Gripping state, adjusting its position by rotating towards the detected object.
2) **Gripping**: The state refers to the condition in which the robot securely holds an object. After successfully completing the gripping action, the robot transitions to the "Placing" state, where it moves the object to its designated location.
3) **Placing**: The state refers to the phase in which the robot positions an object at a designated location and subsequently returns to its initial position following the completion of the Gripping State. During this process, the robot's rotational angle varies between 50 and 145 degrees, contingent on the location of the target object.

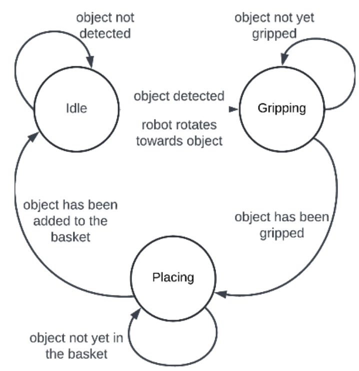


Fig. 3. State diagram model.

Meanwhile FLC model we proposed is employed to adjust the robot arm's angle to pick the target accurately. The controlling principle of fuzzy-logic method involves one or more inputs and results in one or more outputs to be process for the next step. The fuzzy control basic structure includes fuzzification unit, fuzzy inference system, knowledge base as well as defuzzification unit [66]–[71]. As the notion of fuzzy logic is based on uncertainty, an idea of having an empirical formula to determine membership function defies with the generalized applicability of the fuzzy logic system. Optimization of membership function has always been a field of research in fuzzy logic systems [72]–[74].

In this study, the input of this fuzzy model is the position of the object detected by the Pixy2 CMUCam5, which is defined as (x,y) in pixels unit. The output of this fuzzy model is the inclination angle of the robot arm (θ). This output consists of two angles that will control the servo motor, corresponding to the robot arm's horizontal and vertical positions, allowing it to grasp the targeted object precisely.

After determining the inputs and outputs of the fuzzy model, the next step is to define the membership functions. The membership function is utilized to categorize input and output parameters into distinct categories. The membership function for the input variable (x) is classified into three distinct categories: left, center1, and right. Meanwhile, the input (y) is categorized into three regions: top, center, and bottom. In general, the input parameters are represented by images captured by the camera, which are divided into nine grids, as illustrated in Fig. 4. The values of the membership functions for the inputs are presented in Table I and Table II, represented as mathematical equation models.

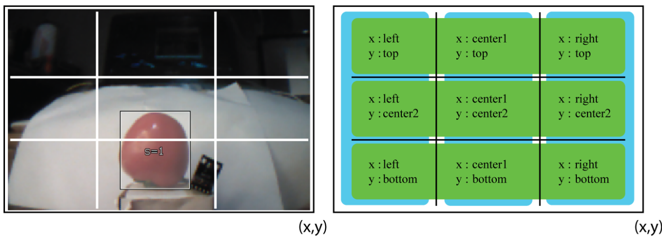


Fig. 4. Illustration of input's membership function.

TABLE I. MEMBERSHIP FUNCTION OF INPUT x

Linguistic Term (x)	Equation
Left	$\mu_{left} = \begin{cases} 1 & ,x \leq 70 \\ \frac{100-x}{30} & ,70 \leq x \leq 100 \\ 0 & ,x \geq 100 \end{cases}$
Center1	$\mu_{center1} = \begin{cases} \frac{x-70}{30} & ,70 \leq x \leq 100 \\ 1 & ,100 \leq x \leq 130 \\ \frac{180-x}{50} & ,130 \leq x \leq 180 \end{cases}$
Right	$\mu_{right} = \begin{cases} \frac{x-130}{50} & ,130 \leq x \leq 180 \\ 1 & ,x \geq 180 \\ 0 & ,others \end{cases}$

TABLE II. MEMBERSHIP FUNCTION OF INPUT y

Linguistic Term (y)	Equation
Top	$\mu_{top} = \begin{cases} 1 & ,x \leq 55 \\ \frac{70-x}{15} & ,55 \leq x \leq 70 \\ 0 & ,x \geq 70 \end{cases}$
Center2	$\mu_{center2} = \begin{cases} \frac{x-55}{15} & ,55 \leq x \leq 70 \\ 1 & ,70 \leq x \leq 80 \\ \frac{110-x}{30} & ,80 \leq x \leq 110 \end{cases}$
Bottom	$\mu_{bottom} = \begin{cases} \frac{x-80}{30} & ,80 \leq x \leq 110 \\ 1 & ,x \geq 110 \\ 0 & ,others \end{cases}$

Meanwhile, the output of this fuzzy model is represented by angles, which are utilized to control the movement of the robot arm, enabling precise execution of the picking process. The first is the elbow angle, which enables vertical movement of the robot arm, while the second is the base angle, responsible for its horizontal movement. The elbow angle is classified into three categories: narrow, average, and wide. Likewise, the base angle is divided into three groups: right slant, straight, and left slant. The categorization of the elbow angle from the robot's side view is presented in Fig. 5, while Fig. 6 depicts the categorization of the base angle from the top view. The membership function values for the output are presented in Tables III and IV, represented in the form of mathematical equations.

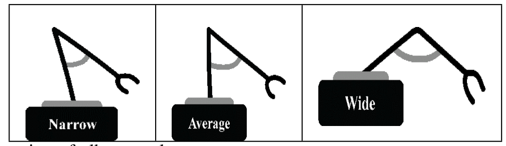


Fig. 5. Illustration of elbow angle.

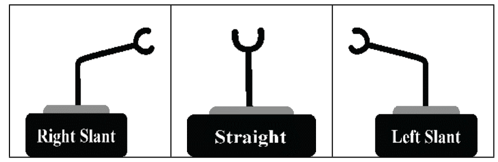


Fig. 6. Illustration of base angle.

TABLE III. MEMBERSHIP FUNCTION OF OUTPUT ELBOW

Linguistic Term(θ_1)	Equation
Narrow	$\mu_{narrow} = \begin{cases} 1 & ,x \leq 75 \\ \frac{95-x}{20} & ,75 \leq x \leq 95 \\ 0 & ,x \geq 95 \end{cases}$
Average	$\mu_{average} = \begin{cases} \frac{x-75}{20} & ,75 \leq x \leq 95 \\ 1 & ,95 \leq x \leq 105 \\ \frac{110-x}{5} & ,105 \leq x \leq 110 \end{cases}$
Wide	$\mu_{wide} = \begin{cases} \frac{x-105}{5} & ,105 \leq x \leq 110 \\ 1 & ,x \geq 110 \\ 0 & ,others \end{cases}$

TABLE IV. MEMBERSHIP FUNCTION OF OUTPUT BASE

Linguistic Term(θ_2)	Equation
Left Slant	$\mu_{left_slant} = \begin{cases} 1 & ,x \leq 70 \\ \frac{90-x}{20} & ,70 \leq x \leq 90 \\ 0 & ,x \geq 90 \end{cases}$
Average	$\mu_{straight} = \begin{cases} \frac{x-70}{20} & ,70 \leq x \leq 90 \\ 1 & ,90 \leq x \leq 100 \\ \frac{105-x}{5} & ,100 \leq x \leq 105 \end{cases}$
Right Slant	$\mu_{rightslant} = \begin{cases} \frac{x-100}{5} & ,100 \leq x \leq 105 \\ 1 & ,x \geq 105 \\ 0 & ,others \end{cases}$

After establishing the membership function, the subsequent step involves modeling a fuzzy rule-based system, which acts as a reference framework for decision-making within the fuzzy logic system. The fuzzy model is composed of nine potential rules, which are presented in detail in Table V. The rule-based system is logically defined by correlating the output results with the corresponding input data. For example, in Rule number one (R1), if the detected input corresponds to the object's position in the upper-left area of the image (left and top), the output angles necessary for the robot to accurately grasp the target would be a base angle categorized as 'left slant' and an elbow joint classified as 'wide. The output, which is still in the defuzzification stage, produces a numerical angle value.

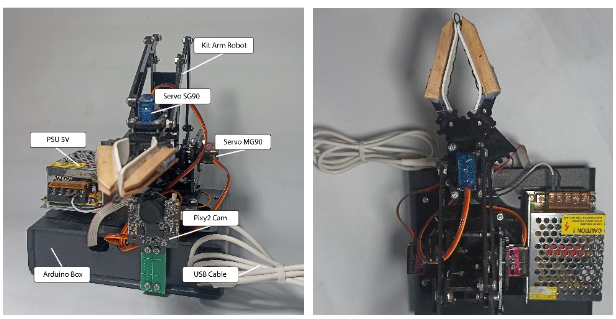
III. RESULTS AND DISCUSSION

In this study, we developed a prototype of a robotic gripper specifically designed for harvesting tomatoes. The system

TABLE V. FUZZY RULE BASED

Rule	Input		Output	
	x	y	Base	Elbow
R1	Left	Top	Left Slant	Wide
R2	Left	Center	Left Slant	Average
R3	Left	Bottom	Left Slant	Narrow
R4	Center	Top	Straight	Wide
R5	Center	Center	Straight	Average
R6	Center	Bottom	Straight	Narrow
R7	Right	Top	Right Slant	Wide
R8	Right	Center	Right Slant	Average
R9	Right	Bottom	Right Slant	Narrow

integrates a Finite State Machine (FSM) model to control the robot's behavior, while a Fuzzy Logic Controller (FLC) model was implemented to ensure precise movement of the robotic gripper. The prototype is capable of harvesting tomatoes with a maximum width of 5 cm and a height of up to 7 cm. Fig. 7 presents both front and top views of the system developed in this research. The constructed gripper robot successfully meets the initial design specifications and requirements. Upon completion of the implementation, several tests were conducted to assess the performance of the proposed system.



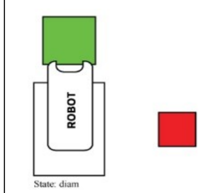
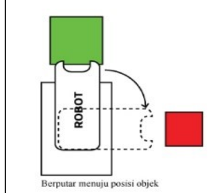
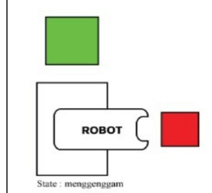
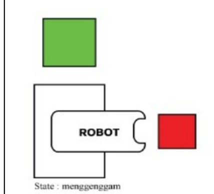
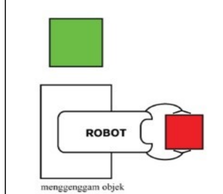
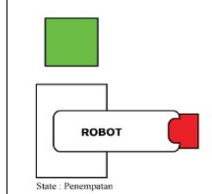
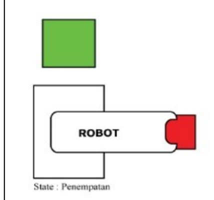
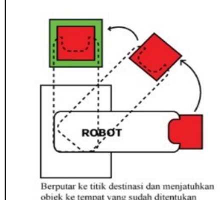
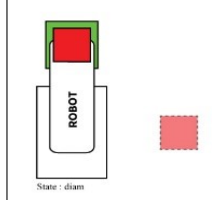
(a) (b)

Fig. 7. A prototype of robotic gripper implemented in this study (a) front view; (b) top view.

The performance evaluation of each component of the robot gripper revealed that the Pixy2 CMUCam5 successfully detected tomato objects at a maximum range of 40 cm under varying light intensities, ranging from 25 to 3000 lux. Furthermore, the data transmission between the Pixy2 camera and the Arduino was tested and confirmed to function effectively. Servo motor testing was also conducted to assess the accuracy of the angles generated. The results demonstrated that the servo motor operated efficiently, achieving an accuracy of 99.7%.

Several studies that have developed FSM methods for modeling robot behavior have demonstrated optimal performance outcomes [75]. To validate the accuracy of the robot's behavior in accordance with the initial design, the FSM method was implemented and tested, as depicted in the state machine diagram in Fig. 3. The test results, summarized in Table VI, confirm that all state transitions were consistent with the state diagram initially defined during the modeling process. These findings suggest that the robot's behavior aligns effectively with its original design specifications.

TABLE VI. FSM MODEL TESTING ON ROBOTS

Robot Initial State	**Action**	**Robot Final State**
 State: Idle	 Action: Robot rotates towards target	 State: Gripping
 State : Gripping	 Action: Robot gripped the object	 State:Placing
 State : Placing	 Action: Robot rotates towards the destination point	 State:Placing

In tomato harvesting, a critical factor determining the success of the picking process is the accuracy of the robot arm's angle. This angle is precisely calculated using fuzzy logic control. A case study was conducted by selecting a specific object position, followed by experimental testing. The experimental results were then compared with simulation data. A comparison of the robot arm angles obtained from the experiment and the simulation is presented in Table VII. According to Table VII, the error rate for the elbow angle is 1.004%, while for the base angle, it is 0.826%. These findings demonstrate that the fuzzy logic model implemented in the robot has performed effectively.

TABLE VII. COMPARISON OF FUZZY MODELS ON GRIPPER ROBOTS AND SIMULATION

Input (x, y)	Ouput	Proposed System	Simulation
(158, 153)	Elbow Angle	69.0	69.7
	Base Angle	72.0	72.6

The comprehensive performance testing of the gripper robot was conducted, as illustrated in Fig. 8. In this testing, ten trials were performed, each with different object placements. In all ten trials, the robot successfully completed the task of picking tomatoes. Fig. 8 provides a detailed illustration of the overall performance testing process for the robotic system.

(a) (b)

Fig. 8. Scenario testing of picking tomatoes (a) front view; (b) top view.

The performance of the proposed method was evaluated by comparing the robot gripper's performance using a FSM and FLC model against a gripper without FLC (Non-FLC). The tests were conducted using 10 different positions, as shown in Table VIII. Based on this results, the robot gripper utilizing the FSM and FLC model achieved a 100% success rate in grasping the target, whereas the Non-FLC gripper achieved only a 20% success rate.

TABLE VIII. COMPARISON OF FUZZY MODELS ON GRIPPER ROBOTS AND SIMULATION

No	Input (x, y)	FLC	Non FLC
1	(70, 66)	Failed	Success
2	(98, 99)	Failed	Success
3	(94, 153)	Failed	Success
4	(163, 65)	Failed	Success
5	(161, 99)	Success	Success
6	(158, 153)	Success	Success
7	(248, 49)	Failed	Success
8	(262, 101)	Failed	Success
9	(262, 101)	Failed	Success
10	(253, 153)	Failed	Success

The implementation of the FLC model in controlling the robot's positioning significantly enhanced the gripper's performance for tomato picking. This improvement is attributed to the more diverse range of outputs generated by the FLC compared to the Non-FLC model. Additionally, the increased accuracy provided by the FLC method is partly due to the proper modeling of input and output membership functions, which are essential for accurate categorization. For future research, we recommend incorporating fuzzy control to regulate grasping force during tomato harvesting, similar to previous studies on strawberries [76].

The success of this experiment is partly due to the consistent light intensity maintained during testing. Since the camera used to detect objects is influenced by light intensity, future research is needed to develop a more robust system capable of functioning under varying lighting conditions. This can also be enhanced by integrating machine learning technology to address these limitations.

IV. CONCLUSION

In this study, a robotic arm control system was successfully developed using a Pixy2 CMUCam5, an Arduino Uno microcontroller, and servo motors. The results demonstrate that the hybrid model combining a Finite State Machine (FSM) and Fuzzy Logic Controller (FLC) is effective in controlling the robotic arm's behavior and adjusting the gripper's angle to perform tasks such as grasping tomatoes.

The FSM model designed in this research was successfully implemented and produced behaviors consistent with the specified system requirements, enabling it to perform tasks efficiently. Comparisons between FSM model testing and simulation results showed minimal error, indicating that the FLC model was effectively implemented. Further system performance tests compared the robotic gripper's performance using the hybrid FSM-FLC method with the hybrid FSM-Non FLC method. The results indicate that the system utilizing the fuzzy logic approach outperformed the non-fuzzy method. These findings suggest that the combination of FSM and FLC in a hybrid model significantly improves the accuracy of the robotic system in harvesting tomatoes.

With the improvement in accuracy, this development enables the creation of a robotic gripper system that can assist in the automatic fruit-picking process, thereby reducing labor costs. Future developments could involve transforming the robotic gripper into a mobile robot, allowing it to operate more efficiently.

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