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Autonomous visual servoing for alternately working arm robots

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Abstract

Robots have infiltrated many aspects of human life up to this point, and with the term Industry 4.0, robots have even become the primary workforce in various factories. This condition necessitates that the robots collaborate without clashing. This paper discusses the application of two arm robot manipulators working alternately in sorting agricultural products. The proposed method employs simple image processing to detect the object and becomes the input to the system to control the robots. The effectiveness of the proposed method is enhanced by the application of a Fuzzy Logic Controller to smoothen robots' joints motions. The average time required by the robot to finish their task from detecting to returning to standby position is 11.76 s for green tomatoes and 12.86 s for red tomatoes. The experimental results show that the proposed method is effective in controlling two robots to pick and place agricultural products using visual servoing.

1. Introduction

Robots are progressively deployed in all sectors of life, both in industry and in everyday life. The purpose of robots is also expanding, beginning with merely assisting people working in a challenging, dangerous, and dirty area, and currently progressing to the point where robots are the primary employees in factories, with humans acting only as monitors and supervisors [1]. Technological advancements are the primary reason for the increasing use of robots in human life. The fundamental benefit of technological advancements is that more components exist for building robots, ranging from high-spec and expensive components to low-cost yet effective ones. A camera is an example of components or sensors used by robots to replace human vision. Cameras are not only becoming more affordable, but they are also becoming smaller, allowing them to be easily installed on robots without adding extra weight.

Therefore, it is getting more accessible and affordable to build robots, which can be customized according to their deployment area, such as agricultural robots [2][3][4][5]. Agricultural robots can be simple robots moved by motors and equipped with eyes to see the object to be manipulated. One of the examples of agriculture robots is a robot assigned to pick agricultural commodities during the post-harvesting handling, such as tomatoes and oranges, as discussed by Dewi et al. in 2020 [5]. This robot relies on its eye to distinguish the objects to be manipulated, and it can determine which object to take or ignore via simple image processing [2][3][4][5][6][7][8][9][10][11][12]. The process of controlling a robot by using input from object detection is called visual servoing.

Visual servoing takes features from the robot's workspace, such as robot coordinate and the object's position to be manipulated. This method controls the position of the robot's end-effector relative to the target [12][13][14][15][16][17][18][19][20][21]. There are two types of camera installation, the eye-to-hand or eye-in-hand camera, depending on the camera's location applied to the system. Eye to hand is where the camera is installed elsewhere, such as on the wall or ceiling. Eye in hand is when the camera is attached to the end-effector.

There is a discussion about Industry 4.0, and even in some countries has been implemented [1]. This new technology revolution proposes the 100% automatic factory, where the primary workers are robots. It is preferable having a group of simple robots working together rather than one sophisticated robot [19]. It is vital to arrange for the robots to operate together without crashing. One method for getting robots to cooperate with each other is to install an "eye" on the robot, allowing it to observe its task and only do what it needs to accomplish [22][23][24][25][26][27]. Two robots or multiple robots [20][21] working together are different from a dual-arm robot. The dual-arm robot is a robot equipped with two arms [24][25][26][27]. The current research in visual servoing is employing one robot, such as Ahlin et al. in 2016 conducted visual servoing to detect leaves [12]. Another method of visual servoing is implementing it to a dual-arm robot, such as Ling et al. implementing image processing to detect tomatoes to be harvested [15][28]. The current research considered static targets, such as discusses by Hou et al. in 2021 [4]. The current research of visual servoing for multi robots is limited to simulation, such as presented by Huang et al. in 2015 [29].

The challenging strategy of image processing is that it needs specific computer memory resources, such as Chen et al. in 2021 [5] used a laptop to be the controller [4][5][6][7][11][13]. Hence, implementing simple image processing but effective enough to differentiate the target and its background can solve this problem. Image segmentation, blob analysis, and edge detection are various image processing commonly used in visual servoing, giving their easy implementation and not require a high resource processor. These image processing methods can be accommodated by the limited memory capacity of microcontrollers widely available in the market, such as Raspberry Pi and Arduino [3][8][21].

This paper proposed the application of visual servoing to control two arm robot manipulators working alternately to pick and place tomatoes. One robot is assigned to pick the red tomato, and another is to pick the green one. A fuzzy logic controller (FLC) is implemented to improve arm robot performance [30][31][32]. The novelty of this research is that it considers moving targets. The experimental testbed consists of two arm robot manipulators with the same specification technique. The experiment will be conducted to prove the effectiveness of the proposed method.

2. Research Method

This study proposes the design of two-arm robot manipulators that works alternately in an industrial scenario. These robots are assigned to work in agricultural commodity post-harvest handling. The agricultural goods considered in this study are red and green tomatoes. One robot is tasked with picking and placing red tomatoes from the belt conveyor into the basket, while the other is to sort the red tomatoes. The robots take turns doing their assigned tasks based on image detection input from the eye-to-hand camera mounted to the belt conveyor.

2.1 Mechanical and Electrical Design of Arm Robot Manipulator

The arm robot manipulators considered in this study are equipped with a proximity sensor attached to the end-effector, and both consider the input from image detection from the camera mounted on the belt conveyor or using the eye-to-hand method. The block diagram of input and output is given in Figure 1, where the inputs are object detection provided by image processing getting input from the camera and distance from the proximity sensor. The outputs are servo motors installed on robots' joints and end-effectors. The image processing using image segmentation is conducted in Raspberry Pi. As the camera captures images giving the input to Raspberry Pi and image segmentation differentiate the assigned target from its background. This detection gives the coordinate position of the targets, and this position is sent to the microcontroller and moves the servo motors. The FLC for target selection and coordinate position detection is conducted in Raspberry Pi, and input from the proximity sensor is for FLC in the microcontroller.

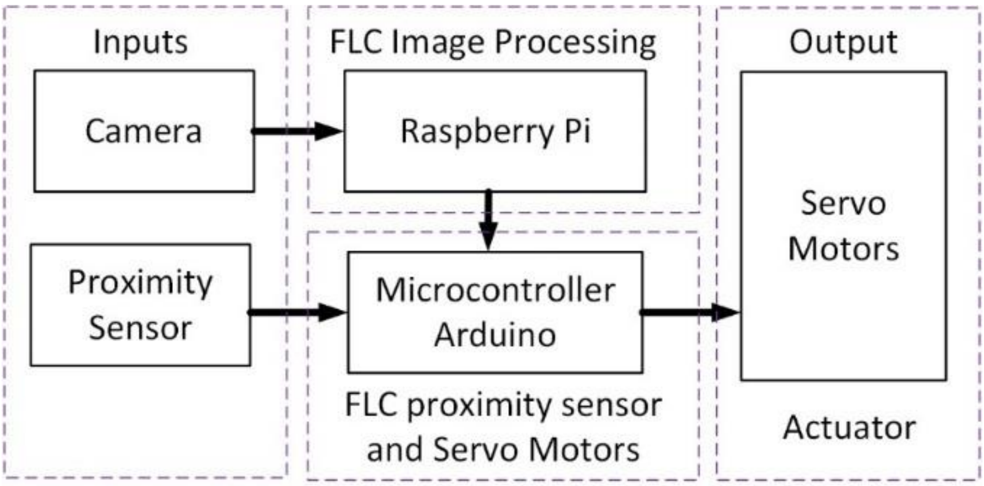
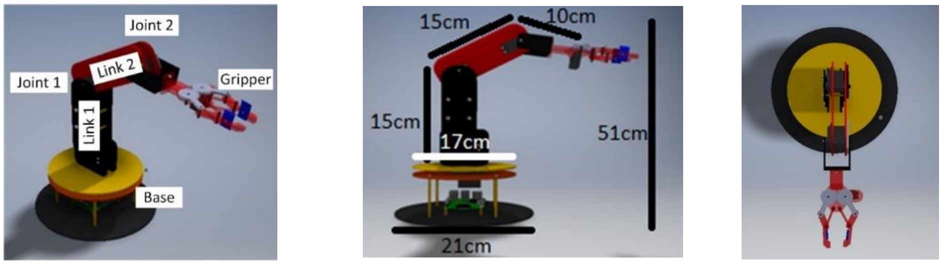


Figure 1. Input and Output Diagram of Robots Considered in this Study

The mechanical design of the two robots is shown in Figure 2. Robots' base, joints, links, and gripper are defined in Figure 2(a), Figure 2(b) shows the robot's dimension, and Figure 2(c) depicts an aerial view of the robot. Table 1 shows the minimum and maximum angle of servo motors installed on the robot where servo motor 1 moves the base, servo motor 2 in joint 1, servo motor 3 in joint 2, and servo motor 4 opens and closes the gripper.



(a) Links, joints, and end-effector *(b) Robot's dimension* *(c) Robot's head view*

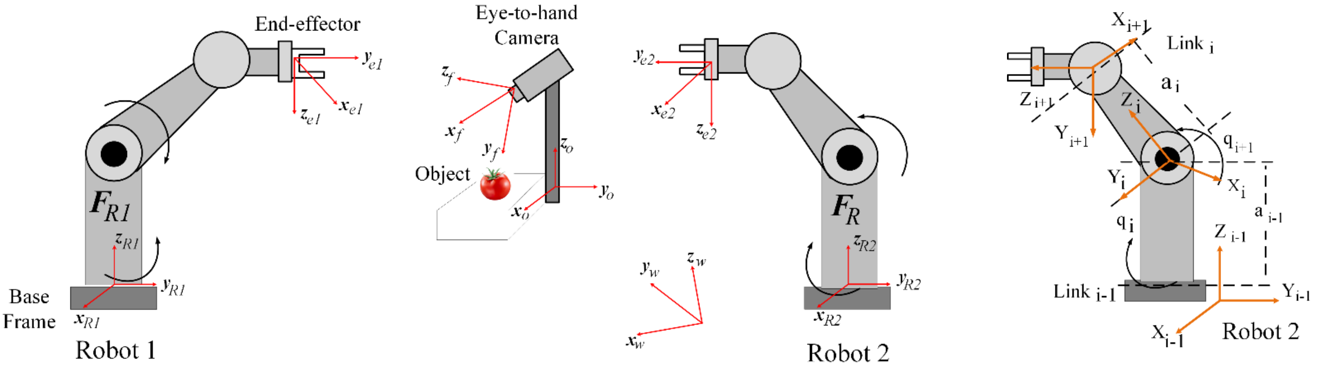
Figure 2. Mechanical Design of Robots Considered in this Study

Table 1. Robots' Motion Specification

Link-n	Minimal	Maximum
Base	0°	180°
Joint 1	10°	180°
Joint 2	30°	180°
Gripper (End-Effector)	4 cm	5 cm

2.2 Visual Servoing Design

Visual servoing is a way of directing a robot utilizing input from object detection provided by a camera. This study utilized the Position-based Approach, in which the robot moves using the input from object detection resulted from the image processing. The estimation of robot position and orientation from camera trajectories can be integrated with robot control during an obstacle avoidance strategy. Figure 3(a) depicts the visual servoing settings of two arm robot manipulators, and the camera employed in this study is an eye-to-hand camera setup. Figure 3(b) illustrates the frame assignment of each link and joint of the robot in Figure 3.



(a) Visual servoing setting *(b) Frame assignment*

Figure 3. Frame Assignment for Visual Servoing of Two Arm Robot Manipulators Working Alternately

The arm robots in Figure 3(a) are having the same specification. Therefore, frame assignment analysis is the same as shown in Figure 3(b), where $X_{i-1}, X_i, X_{i+1}, Y_{i-1}, Y_i, Y_{i+1}, Z_{i-1}, Z_i, Z_{i+1}$ are arm robot manipulator coordinates frame, $\alpha_{i-1}$is the link twist, $a_{i-1}a_i$ are the link length, and θ_i, θ_{i+1}, are the joint angle. The kinematic analysis in this study is ignoring the end-effector; hence the robot is considered as 3DOF. The transformation matrix (T_0^3) given in [33] is Equation 1.

$$T_0^3 = \begin{bmatrix} c_{123} & -s_{123} & 0 & c_1(a_0 + a_1c_2 + a_2c_{23}) \\ s_{123} & c_{123} & 0 & s_1(a_0 + a_1c_2 + a_2c_{23}) \\ 0 & 0 & 1 & d + a_1s_2 + a_2s_{23} \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & P_x \\ r_{21} & r_{22} & r_{23} & P_y \\ r_{31} & r_{23} & r_{33} & P_z \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (1)$$

Where c_i is $\cos\theta_i$, s_i is $\sin\theta_i$, c_{ij} is $\cos(\theta_i + \theta_j)$, s_{ij} is $\sin(\theta_i + \theta_j)$, c_{ijk} is $\cos(\theta_i + \theta_j + \theta_k)$, s_{ijk} is $\sin(\theta_i + \theta_j + \theta_k)$and r_{lm} is the rotational element, l, m, for example, $c_1$is $\cos\theta_1$, c_{12} is $\cos(\theta_1 + \theta_2)$, and c_{123} is $\cos(\theta_1 + \theta_2 + \theta_3)$.

The transformation matrix in Equation 1 gives the position robot in x, y, and z-axis, as follow Equation 2.

$$p_x = c_1(a_0 + a_1c_2 + a_2c_{23}) ,\ p_y = s_1(a_0 + a_1c_2 + a_2c_{23}) \text{, and } p_z = d + a_1s_2 + a_2s_{23}. \quad (2)$$

The Jacobian matrix ($J(q)$) derived from robot position in Equation 2 given by [29] is Equation 3.

$$J(q)\dot{q} = \begin{bmatrix} -s_1(a_0 + a_1c_2 + a_2c_{23}) & -c_1(a_1s_2 + a_2s_{23}) & -a_2c_1s_{23} \\ c_1(a_0 + a_1c_2 + a_2c_{23}) & -s_1(a_1s_2 + a_2s_{23}) & -a_2s_1s_{23} \\ 0 & a_1c_2 + a_2c_{23} & a_2c_{23} \end{bmatrix} \quad (3)$$

The Jacobian matrix in Equation 3 gives the translational (ν) and rotational (ω) of the robots as follow Equation 4.

$$J(q)\dot{q} = \begin{bmatrix} \nu \\ \omega \end{bmatrix} = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \omega \end{bmatrix} = \begin{bmatrix} -s_1(a_0 + a_1c_2 + a_2c_{23}) & -c_1(a_1s_2 + a_2s_{23}) & -a_2c_1s_{23} \\ c_1(a_0 + a_1c_2 + a_2c_{23}) & -s_1(a_1s_2 + a_2s_{23}) & -a_2s_1s_{23} \\ 0 & a_1c_2 + a_2c_{23} & a_2c_{23} \end{bmatrix} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} \quad (4)$$

Object detection involves the perspective projection of a target in an image place capture by a camera [34]. The perspective projection of the target object in the image plane is shown in Figure 4, and the relation between 2D coordinates frame in the image plane, and object coordinates frame is Equation 5.

$$u = \lambda\frac{x}{y},\ v = \lambda\frac{y}{z}, \quad (5)$$

Where u and v are the 2D coordinates in image plane and λ is the distance between center of projection to image plane, as shown in Figure 5.

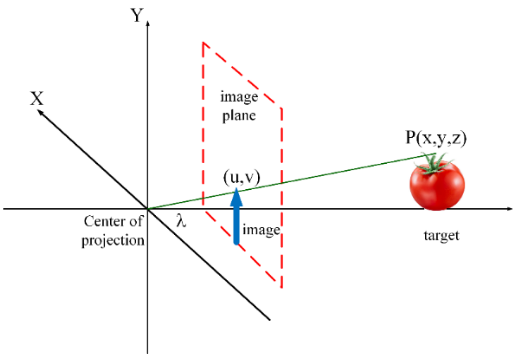


Figure 4. Perspective Projection of an Object in Image Plane

The detected image velocity related to camera velocity (ξ) is Equation 6.

$$\xi = \begin{bmatrix} \nu \\ \omega \end{bmatrix}, \quad (6)$$

Where ν is the translational and ω is the rotational velocity given in Eq. 4. If the vector projection plane is $s(t)$ and $\dot{s}(t)$ is the velocity of the target in image feature [30]. Therefore, the relationship between target object velocity ($\dot{s}(t)$) and camera velocity is Equation 7.

$$\dot{s} = L(s, q)\xi, \quad (7)$$

Where q is robot position given in Equation 2 and L is the image Jacobian matrix as follow Equation 8.

$$L = \begin{bmatrix} -\frac{\lambda}{z} & 0 & \frac{u}{z} & \frac{uv}{\lambda} & -\frac{\lambda^2 + v^2}{\lambda} & v \\ 0 & -\frac{\lambda}{z} & \frac{v}{z} & \frac{\lambda^2 + v^2}{\lambda} & -\frac{uv}{\lambda} & -u \end{bmatrix}. \quad (8)$$

Hence, the image Jacobian interaction matrix in Equation 8 can be expressed as follow Equation 9.

$$\dot{s} = L_v(u, v, z)v + L_\omega(u, v)\omega. \tag{9}$$

The image processing conducted in this study is image segmentation for green tomatoes and edge detection for red tomatoes. Image segmentation divides an image acquired by a camera into various segments or groups of pixels to define an image's representation into a set of boundaries such as curves and lines. All the assigned pixels are tagged to discover pixels with the same properties, such as color, intensity, and texture. The image segmentation can also be limited to separating the foreground region from the background region of interest. Hence, the image is divided into higher than the threshold value as 1 and lower than the threshold value as 0.

2.3 Fuzzy Logic Controller Design

In this study, a triangle curve is employed to construct a function variable from fuzzy membership logic inputs: image detection by camera sensors and proximity sensors, and four outputs from servo motors in each installed link. These variables and settings are applied to the 4DOF robot arm. Table 2 shows the rules-based design to show the relationship between input and output of robots in Figure 2. The membership function of inputs is given in Figure 5(a), and the output membership function is in Figure 5(b).

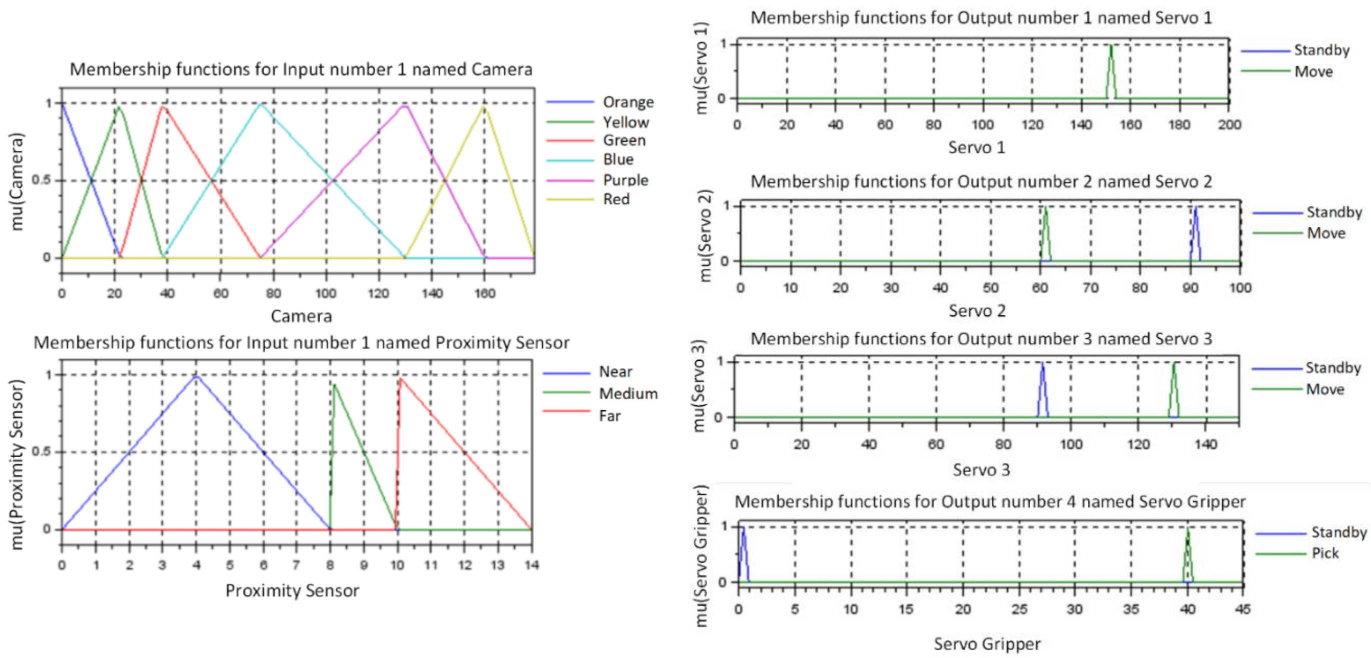
Figure 5(a) shows the inputs from object detection by camera and distance by proximity sensor. The first input is a camera sensor consisting of 7 fuzzy color sets, where; Red (0-22), Yellow (22-38), Green (38-75), Light Blue (75-130), purple (130-160), Red (160-179) and the second input proximity sensor; where near (1-8), Medium (8-10), Far (10-14). Figure 5(b) is the membership function of output where variable servo motor 1 is installed in robot base, servo motor 2 in link 1, servo motor 3 in link 3, and servo motor 4 is to move gripper. The fuzzy set of the gripper is given as Standby, Move, and Pick as the language to control the robot. The fuzzy set output of servo motors installed on the links are Standby for servo motor 1 is 150^{O}, and servo motors 2 and 3 are 90^{O}. Variable Move and Pick for servo motor 1 is 150^{O}, servo motor 2 is 60^{O}, servo motor 3 is 130^{O}, and servo motor 4 is 40^{O}.

Fuzzification is a rule employed in a fuzzy system that turns the input value or input whose truth value is definite (crisp input) into fuzzy, which is the linguistic value used in the form of red, yellow, green, and so on based on the function of a particular membership. Following further fuzzification is inference that is reasoning that uses fuzzy input and previously determined fuzzy rules to produce fuzzy output. The inference used in this study is IF camera sensor AND proximity sensor THEN servo motor Pick.

Table 2. Rule-based used to Control the 4DOF Arm Robot in this Study

Camera Sensor	Proximity Sensor	Servo Motor 1	Servo Motor 2	Servo Motor 3	Servo Motor 4
Orange	Near	Standby	Standby	Standby	Standby
Orange	Medium	Standby	Standby	Standby	Standby
Orange	Far	Standby	Standby	Standby	Standby
Yellow	Near	Standby	Standby	Standby	Standby
Yellow	Medium	Standby	Standby	Standby	Standby
Yellow	Far	Standby	Standby	Standby	Standby
Green	Near	Move	Move	Move	Pick
Green	Medium	Standby	Move	Move	Standby
Green	Far	Standby	Move	Move	Standby
Blue	Near	Standby	Standby	Standby	Standby
Blue	Medium	Standby	Standby	Standby	Standby
Blue	Far	Standby	Standby	Standby	Standby
Purple	Near	Standby	Standby	Standby	Standby
Purple	Medium	Standby	Standby	Standby	Standby
Purple	Far	Standby	Standby	Standby	Standby
Red	Near	Standby	Standby	Standby	Standby
Red	Medium	Standby	Standby	Standby	Standby
Red	Far	Standby	Standby	Standby	Standby

The rules of a fuzzy logic arm robot with 4DOF are designed to detect one color from a set of six color ranges. The proximity sensor can detect the distance up to 8 cm as the closest range to the end-effector. As the robot detects green tomato, the arm robot moves, and if the distance from the robot to the green tomato is 8cm, the end effector picks the tomato. The rules are assigned to red tomatoes with a different range of color detection.



(a) Membership function of inputs (b) Membership function of outputs

Figure 5. Membership Function of Input and Output of FLC Considered in this Study

3. Results and Discussion

This study discusses the application of position-based visual servoing applied to two arm robot manipulators working alternately in sorting red and green tomatoes in post-harvesting agricultural products. The robot is taking a turn in pick and placing the agricultural product based on their assigned task. The agricultural products to be sorted are placed in the belt conveyor; therefore, the speed of picking up is essential to ensure the robots do not miss the product. Robots are equipped with a proximity sensor in their end-effector to avoid crashing the belt-conveyor or the product, as shown in Figure 6. Figure 6 shows the experimental testbed as the realization of working robots in Figure 3, where two robots are working alternately. Robot 1 and 2 workspaces are not colliding; hence, there will be no collision between the two robots.

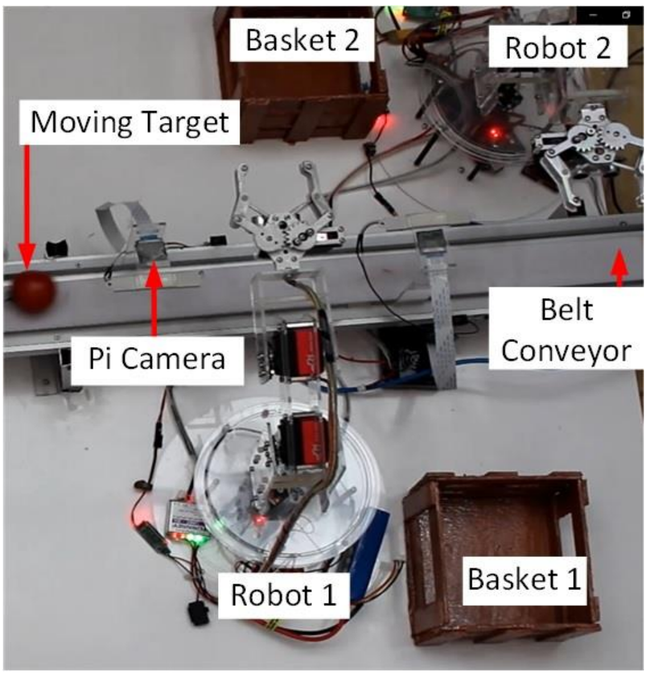
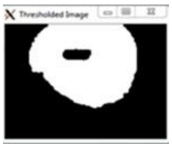
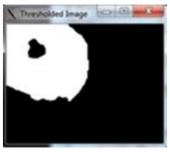
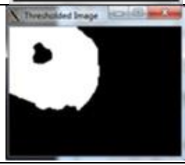
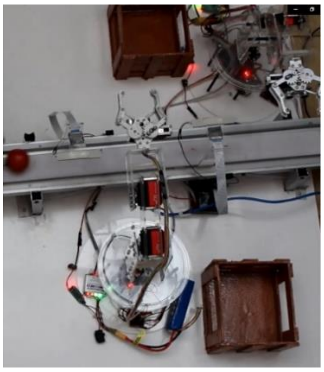


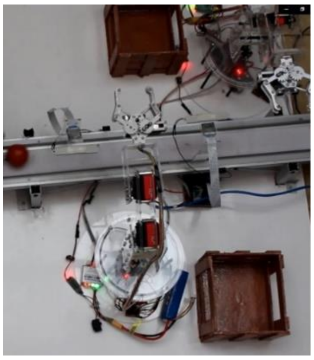
Figure 6. Experimental Test Bed to Verify the Effectiveness of the Proposed Method

Table 3. Red and Green Tomatoes Detection

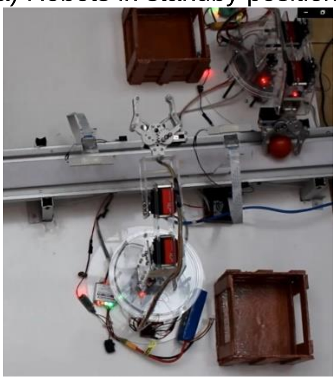
No	Green Tomatoes			Red Tomatoes			Robot Motion
	Raw Image	Detected Image	Tomato Coordinate (x,y)	Raw Image	Detected Image	Tomato Coordinate (x,y)	
1			(190,46)			(196,80)	Approaching belt-conveyor
2			(121,58)			(120,77)	Picking up the tomato
3			(61.54)			(38.82)	Picking up the tomato

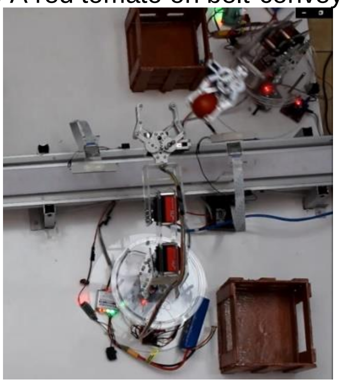
The visual servoing method considers input from image proceeding to recognize the moving tomatoes, either the green or the red tomatoes. Image detection gives green or red tomatoes coordinate position as shown in Table 3. Table 3 shows 3 possibilities of tomato detection, the first tomato position (No 1) is when the tomato starts to enter the camera image plane (green tomato (190,46), red tomato (196,60)), these positions lead the robot to start approaching belt conveyor. The 2nd and 3rd tomatoes positions (No 2 and 3 of Table 2) show the two possible tomatoes positions. No 2 shows that the tomatoes right in the center of the image plane, and No 3 shows the tomatoes are leaving the image plane. No 2 and 3 have the same effects on robots, which are robots picking up the tomatoes.

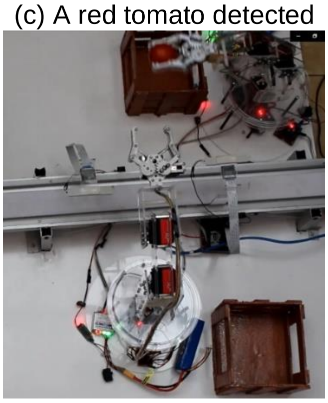

(a) Robots in standby positions


(b) A red tomato on belt-conveyor


(c) A red tomato detected


(d) Robot 2 picks red tomato


(e) Robot 2 moves red tomato


(f) Robot 2 places red tomato

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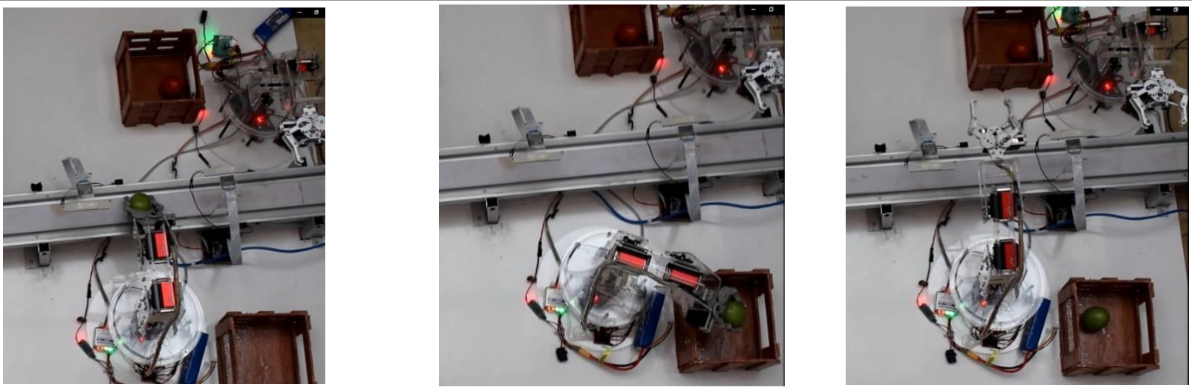


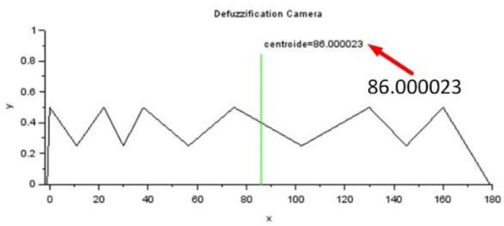
(g) Green tomato is picked by robot 1 (h) Green tomato is placed (i) Robots in standby positions

Figure 7. Video Screenshots of Arm Robots Working Alternately Pick and Placing Tomatoes

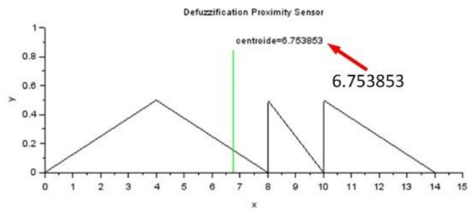
Figure 7 shows the screenshots of robots picking and placing tomatoes. Tomatoes are positioned in a belt conveyor; therefore, the considered target in this study is a moving object. This task is more complicated than detecting and picking a static target, as presented in Dewi et al. in 2019 [8]. Robot 1 is assigned to pick a green tomato and place it in basket 1, and robot 2 is assigned to pick a red tomato and place it in basket 2. This process is repeated for three different red and green tomatoes to ensure the repeatability of the robots designed in this study. The time needed for the robots to complete their tasks is presented in Table 4. The process is timed as the tomato moves on the belt conveyor; hence, as shown in Figure 7, the robot picking green tomato robot is moving to take and place tomatoes. Robot assigned is including the time of robot receiving tomato's x and y coordinate, the time camera detecting and robot picking and placing the target, and robot completing the task and going back to standby position.

Table 4. Time Required to Detect, Picking, Placing and Return to Standby Position

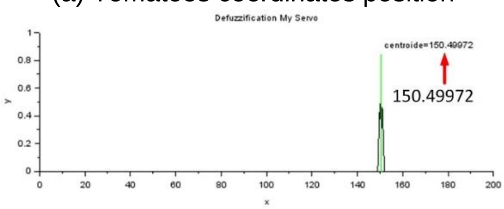
No	nth-Exp	Green Tomatoes			Red Tomatoes		
		Detecting to Picking (s)	Detecting to Picking and Placing (s)	Detecting to Picking, Placing, and Standby(s)	Detecting to Picking(s)	Detecting to Picking and Placing (s)	Detecting to Picking, Placing, and Standby (s)
Tomato 1	1	3.69	9.81	12.46	5.28	11.43	13.23
	2	3.72	9.15	11.53	5.15	10.27	12.84
	3	3.94	9.37	11.72	5.69	10.86	12.57
Tomato 2	1	3.72	9.00	11.45	5.32	11.20	12.97
	2	4.21	9.67	11.80	5.29	10.29	12.96
	3	3.97	9.37	11.61	5.29	10.12	12.75
Tomato 3	1	3.93	9.45	11.82	5.57	10.27	13.02
	2	3.90	9.38	11.64	5.24	9.93	12.74
	3	3.93	9.38	11.77	5.14	10.00	12.70



(a) Tomatoes coordinates position

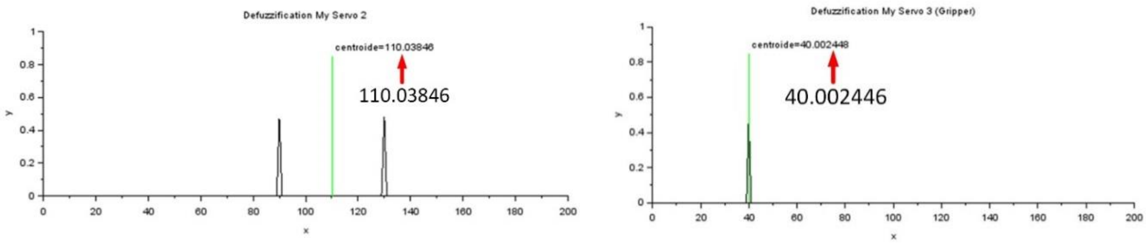


(b) Distance of proximity sensor and tomato



(c) Angle of motor servo 1

(c) Angle of motor servo 2



(c) Angle of motor servo 3 (c) Angle of motor servo 4

Figure 8. Defuzzification Analysis of Robot Motion During Picking and Placing Tomato

Figure 8 shows the defuzzification analysis of arm robot manipulator during picking and placing tomatoes. This defuzzification prove that robots follow the rules assigned in Table 2. Robot motions are based on input shown in Figure 5(a) and output shown in Figure 5(b). If object detection gives 86.000023 and proximity sensor is 6.753853, the robot is picking and placing tomatoes (angle of joint 1 is 150.49972^{O} joint 2 is 75.002381^{O}, joint 3 is 110.03846^{O}, and servo motor attached to gripper opens in 40.002448^{O}). These properties are in line with the specification shown in Table 1.

The experimental results show that the proposed method is effective in controlling two robots to pick and place agricultural products using visual servoing.

4. Conclusion

This paper presents a visual servoing to control two autonomous robots working alternately in sorting agriculture products. One robot is assigned to pick and place green tomatoes, and another is to sort red tomatoes. The FLC is implemented to enhance image processing in Raspberry Pi. The FLC is also applied in the microcontroller Arduino to smooth the robot's arm motion. The image processing is made simple to accommodate the limited memory of microcontrollers available in the market. The effectiveness of the proposed method is verified by experiment using the experimental testbed of two robots with the exact same specifications. The average time required by the robot to finish their task from detecting to returning to standby position is 11.76 s for green tomatoes and 12.86 s for red tomatoes. The experimental results show that the proposed method is effective in controlling two robots to pick and place agricultural products using visual servoing.

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