A Three-dimensional Unit Step Trajectory Plan Model for 6-DOF Robot Arm in Agriculture Harvesting Process

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***Abstract*—Modern agriculture processes use technology to solve the challenges posed by present ecological and environmental changes in agriculture system. Some of the familiar challenges include shortage of skilled formers, and labor work force in the agriculture fields. Fortunately, due to the advancements in electronics, artificial intelligence, and mechatronics, robots are the key in solving majority of these challenges. In recent developments, robots play important role in agriculture forming operations with fast, high accuracy, and continuously replacing manual works done by farmers. For instance, the spraying of pesticides to the plants of agriculture forms continuously may lead to serious health issues for humans such as respiratory problems, whereas the robots can spray efficiently and continuously despite human exhaustion. The modern agriculture form uses robotic arms in the forming operations, especially vertical forming, and horizontal forming methods, as the robot arms are flexible and high accuracy. In this paper, a new model called Three-Dimensional Unit Step Trajectory Plan is presented for modern agriculture harvesting processes. In addition, the paper presents a prototype structure with Six Degree of Freedom (6-DOF) robot arm, sensors, and a microcontroller. A kinematics analysis for the proposed robot arm is presented in the paper. The research methodology develops a trajectory motion plan of 6-DOF robotic arm for the purpose of detecting fruit's ripeness in the plant with fast response time. The paper provides the results of proposed model with analysis.**

***Keywords*—robotics, sensor, Six Degree of Freedom (6-DOF) arm, modern agriculture, fruit harvesting**

I. Introduction

Agriculture is the basis for solving food crisis of the world. In the upcoming decades, there is a lot of demand for plant-based food due to the social lifestyle and health care issues [1, 2]. Furthermore, there is a substantial transformation in the agriculture processes because of the lifestyle of the people. Earlier days, agriculture was carried out in the open fields, whereas in the present days, people show interest in doing the agriculture in indoor forms, vertical forms, and horizontal forms. For these conditions of the forming, robotic technology is much more useful to automate the processes and increase food production. Some of these processes include plantation, sowing, fruit detection, detection of plant health, spraying pesticides, and fruit harvesting [3–8].

Six Degree of Freedom (6-DOF) robot arms are used in many modern agricultures due to their precision tasks, and high accuracy [9–11]. The 6-DOF robot arm behaves like a hand, which can perform moving closely to the object and do the necessary tasks, such as carrying the objects from one place to another place and aligning objects in the required direction. In addition, these robot arms suit the agriculture process. The 6-DOF robot arm contains six servo motors, which help robot arm to make flexible movement around area, and a gripper exists at the end of the robot arm, see Fig. 1. For instance, agriculture harvesting process uses 6-DOF arms used to pluck the fruits and keep it in the basket based on the ripeness of the fruit [12–16].

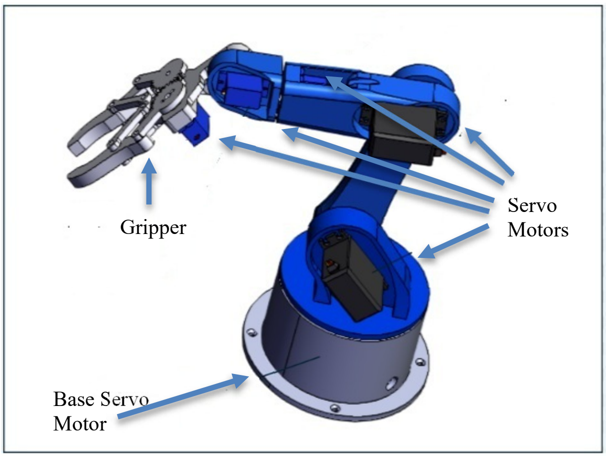

Fig. 1. 6-DOF robot arm.

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In the literature, it shows that the agriculture processes use 6-DOF robot arms for specific crops. For example, the melon crops, tomato forms, and chili crops [12, 13, 15]. Majority of the crops use vision-based algorithms Only Look Once (YOLO), such as YOLOv3, YOLOv5, and YOLOv8 to identify the maturity of fruits. However, these vision-based algorithms pose challenges on the computational processes at the image processing level, which is difficult for the low-capacity microcontrollers, such as Arduino, and raspberry pi. Even though these processors can run complex computations, there is more possibility of delays in computation running time. Despite this, the robot arm trajectory path finding is another challenge. To solve these problems, in this paper, a trajectory motion plan called a three-dimensional trajectory path planning model for the 6-DOF robot arm is presented that can efficiently approach the place, from where the sensor can collect the information for agriculture harvesting process. In addition, the robot assessment process on the ripeness of the fruit is presented in the paper.

The major contributions of the paper are as follows:

- A new trajectory path plan model for the 6-DOF robot arm.
- Identification of fruit ripeness in the plants with fast response time.
- Prototype structure for the 6-DOF robot arm model on fruit harvesting process.

The rest of the paper is organized as follows; Section II presents the related work and literature review, whereas Section III describes the proposed model, and its contributions. Section IV provides the implementation details with results. Finally, Section V concludes the paper.

II. Related Work

Agriculture has become an essential part of the activities for many countries to solve world food scarcity problems. Either due to lack of skilled formers in agriculture or insufficient human work force for the forming process, robotic technology has been an alternative for achieving agriculture processes in fields. In addition, the incorporation of artificial intelligence and machine learning technologies into agricultural processes, the efficiency of agriculture forming is increased and produce high food production [17–22]. The robotic technologies are used in the agriculture processes for various tasks, such as identification of plant's health, fruit harvesting process, fruit counting, identification of soil conditions, and plantation processes [3–8]. Some farmers show interests in adopting technology into the agriculture processes because the crops are highly valuable and farmers are ready to invest in high profits agricultural crops [23, 24]. Moreover, there is lot of demand rise for the world in the upcoming decades due to trouble whether conditions in nature. Hence, it is important to adopt robotic technology to the agriculture forming. Food production needs to be increased in the upcoming decades as there is a lot of demand for food in society due to several reasons, such as increase in the population and high number of natural disasters because of global climate changes. Hence, agriculture uses technology to sustain these challenges [25–28].

The customized robotic systems are built up for specific crops of agricultural systems. For instance, a specialized robotic system was designed for Melon harvesting process [12]. The melon harvester contains a robotic arm, which is located on the base of moving equipment pulled by the tractor. The base area contains two parts. The cartesian manipulator is placed in the second part, which is right behind the first part. The cartesian manipulator can be able to access any location on the field so that it can be able to face the sensor to the melon fruit comfortably. The gripper is attached to the robot arm. The gripper can pluck the fruit because of its flexibility, even at the horizontal motions. The vision systems attached consist of two sensors. The first one is the Far Vision Sensor (FAR), and the second one is Near Vision Sensor (NEAR). The FAR is located in the first area, which can be able to view the overall field area so that it can identify the next melon to be checked. The NEAR sensor is responsible for detecting whether the fruit is ready to pluck or not. The peripheral devices are necessary to protect the image processing equipment, and the covering is necessary to safeguard the image processing equipment from the sunlight.

There was some research on developing the robots for fruit harvesting [29, 30], but fewer works on harvesting green Chile peppers. Some authors proposed a Five Degree of Freedom (5-DOF) arm model to harvest the Chile peppers in the lab setup. The robot arm use Red Green Blue (RGB) camera to identify the fruits. However, it needs human operator to identify the fruits in the images. Deep learning techniques are used in the process of Chile pepper. They used the thermal camera and thermal refractions properties in identification of fruit detection [31].

Hayashi *et al.* [14] proposed a new model for harvesting eggplants using the robotic system. The system is broadly comprised of three units, vision unit, a manipulator unit, and end effector unit. The vision unit is responsible for detecting the eggplant fruit from the tree. The vision unit uses a Charged Coupled Device (CCD) camera, the image processing system, and a PC. The manipulator is responsible for making the vision unit move towards fruit location. The manipulator uses 5-DOF arm model for having the flexibility of movement over the area. The end effector in the system is responsible for plucking the fruit and place it in the designated area. The camera is attached at the middle of the effector, so that it can validate the fruit maturity easily. The machine vision algorithm was used for detecting eggplant fruits based on morphological characteristics and color features.

Kounalakis *et al.* [15] presented a robotic model called greenhouse robot for harvesting tomatoes. The greenhouse robotic system contains a 6-DOF robotic arm, a vision module with depth camera, and the gripper, which is used to cut the tomato from the plant. The system also used a dedicated processor that can help to detect the fruit. The manipulator used in the system is Universal Robot URIDe, which can be controlled by ROS MoveIt [32]. The gripper used for the system contains two jaw pairs. The upper jaw pair is used to cut the tomato peduncle, whereas the lower jaw pair is used grasping.

Pneumatic actuators are used for controlling the jaw pairs. The vision system is composed of Intel RealSense D435 depth camera and one single board PC, Nvidia Jetson Nano, attached behind the 6-DOF robot arm. The tomato object is detected using YOLOv3 algorithm [33]. The ROS package is used in SBC. The detector collects the image and uses bounding box coordinates to identify the object.

Some researchers proposed a robotic arm model that can carry heavy weight crops, such as pumpkin and watermelons [34]. They used 5-DOF robotic arm with maximum payload carrying capacity of 25KG. Umm-e-Aymon *et al.* [9] extended this work by adopting a spherical wrist to the 5-DOF RAVebot-1 robot arm. After adopting the spherical wrist, there is an improvement in Denavit-Hartenburg (DH) parameters, so that it solves the problems of kinematics of forward and inverse movements. The MATLAB is used to validate forward kinematics and inverse kinematics.

The 6-DOF robot arm and vision-based YOLOv3 [35, 36] model can be integrated to recognize objects on a real-time interpretation in an uncomplicated way. For example, a success rate of 65% and an accurate rate of 92% are achieved in the tomato picking procedure. However, challenges with the gripper and pathfinding were noted. Finding secure, safe, and efficient paths is one of the objectives of path detection. Some methodologies for identifying robot path were presented in the literature. The route that the robot will be able to follow based on the coordinate geometry will be chosen [37]. To preserve resources throughout the operation, using the Minimum Spanning Tree (MST) structure in robot path planning is suggested [38, 39]. Some systems account for performance, which is determined by the effectiveness of the gripper and the environment [40]. YOLOv5/v8 was suggested to address the challenge of low object identification accuracy and visibility. In such scenarios, the model may be more suited to greenhouse agriculture settings. One of the goals for using YOLOv8 is the number of issues that can be solved by using deep learning-based implementations [41]. YOLOv8 utilizes enhanced object recognition mechanisms in real-time films. The use of sensor fusion methods in real-time path identification is the goal of some of the solutions. Multipurpose robots that can accomplish a variety of duties such as harvesting, spraying, and inspection were presented [42]. A few of the studies provided datasets that could provide real-time agricultural data for the training and implementation of vision models.

III. Research Methodology

The 6-DOF robot arm is useful for many agricultural processes, such as spraying, object detection, fruit harvesting, and inspection of plant deceases. The 6-DOF arm has high accuracy and flexibility in their forming operations. This section presents a 6-DOF robot arm-based model for the fruit harvesting process. The research methodology for the fruit harvesting process is shown in Fig. 2. Broadly, the entire harvesting process takes place in two stages. The first part makes the robot arm trajectory motion to bring the sensor to the desired location. The second stage takes care of fruit detection using sensing system.

Upon the initiation of harvesting process by the robot arm, it calls arm trajectory motion plan using Algorithm 1. The trajectory motion plan allows the robot arm safely to move to a certain relative destination around its area. Once the robot arm reaches the place where it is convenient for robot arm model to assess the color of the fruit by the color sensor, then the sensor gets the RGB values through the TCS3200, a color sensor recognizer module, which contains 4 Light Emitting Diode (LED) with the input voltage of 5v. If the color of the fruit is red, then the fruit is plucked from the plant and place it in the basket. If the color of the fruit is green, then the robot arm performs no action and goes forward for the next fruit. This process is repeated until fruit harvesting process is completed.

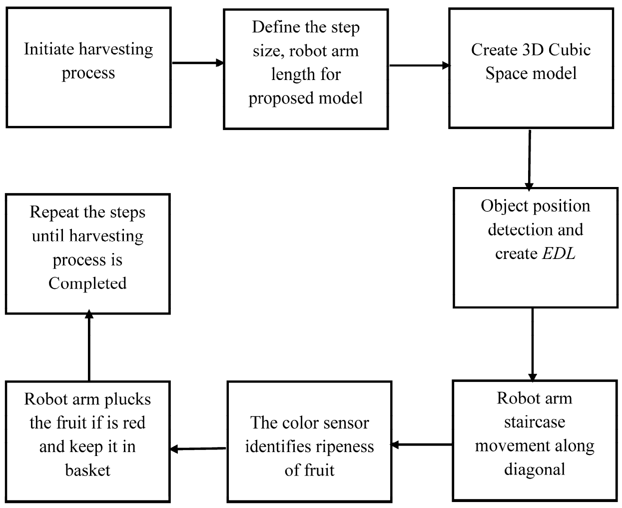


Fig. 2. Research methodology.

For the proposed methodology, the prototype structure is shown in Fig. 3. The robot arm is attached with six servo motors, and a color sensor TS3200 is attached close to the gripper. The gripper needs to be smooth enough to handle the fruit. The position sensor is placed near color sensor to identify the location of the fruit, and it assumes that it is the almost same distance from the color sensor to the fruit.

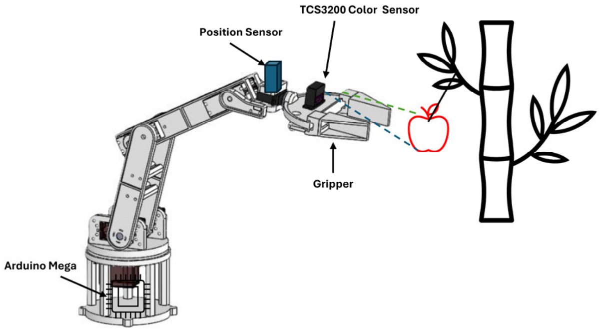


Fig. 3. Prototype structure for proposed model.

The fruit harvesting process is broadly divided into two parts. The first part is responsible for 6-DOF robot arm trajectory motion plan. The paper proposes a new model for the robot arm path plan. The second part is responsible for the detection of fruit's ripeness process. The algorithm for fruit harvesting is shown in Algorithm 2.

Algorithm 1. Trajectory motion plan

1. Identify the robot arm length L. Initialize the staircase step size Δx.
2. Based on the length L, create a 3D cubic space model with the stretch factor $2L$.
3. Sample the 3D cubic space with rows and columns in an interval of Δx.
4. Collect the object location using position sensor and create a *Euclidean Diagonal Line* (*EDL*) from the sensor location to object.
5. The robot arm moves with staircases that are close to the *EDL*. If the slope of *EDL* is zero then no staircases are required, just move the robot arm forward with *EDL*.
6. Upon reaching the robot arm to the predetermined location, the arm movement is stopped.

Algorithm 2. 6-DOF robot arm harvesting

1. Assemble the robot arm and attach the color sensor followed by position sensor.
2. Initiate the robot arm trajectory motion process with *Algorithm 2*.
3. Move the robot arm with staircase model, such that the color sensor needs to face the fruit.
4. Obtain the output of color sensor by collecting fruit's RGB color information.
5. If the color of the fruit is green, then the robot arm performs no action and moves forward for the next fruit.
6. If the color of the fruit is red, then the gripper of robot's arm plucks the fruit and place it in the basket.
7. Repeat the steps from *Step 2* to *Step 6* until the harvesting process is completed.

In Algorithm 2, the step1 is responsible to make the proposed 6-DOF robot arm model ready to take over the fruit harvesting process. Algorithm 1 is used for 6-DOF robot arm trajectory motion path planning.

In Algorithm 1, initially it collects the length of the 6-DOF robot arm. The length of the robot arm can be computed as the sum of individual lengths of the arm rods [43], see Fig. 4.

The robot arm length L is derived for the arm as mentioned in Fig. 4:

$$L = p_1 + p_2 + p_3 + p_4 + p_5 + p_6 \tag{1}$$

where P_i, i =1–5, indicates length of i^{th} robot arm rod, p_6 indicates the length of arm gripper.

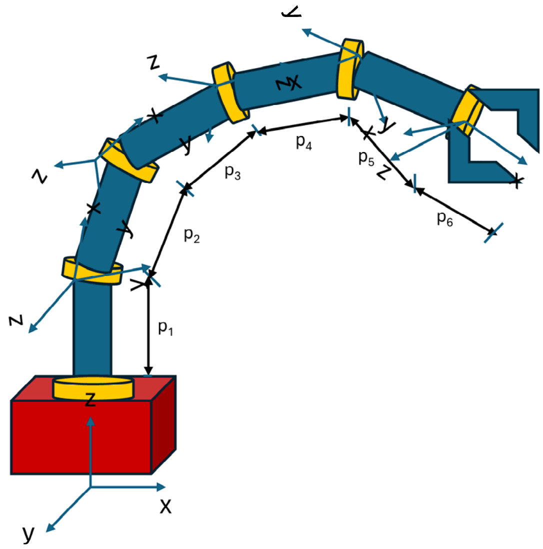


Fig. 4. Measuring the robot arm length.

In other words, the length of the robot arm is the maximum length of arm, which can be obtained by keeping all the arm rods in a straight-line, see the Fig. 5.

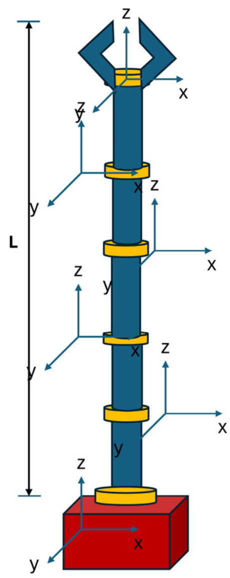


Fig. 5. Robot arm rods in straight line.

Upon obtaining the length of the 6-DOF robot arm, a three-dimensional cube space model is created with each side of $2L$. The center of the 3D cubic model is the base joint of 6-DOF robot arm, see Fig. 6.

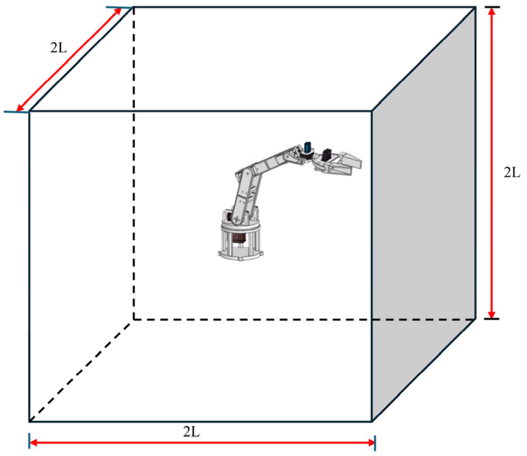


Fig. 6. 3D cubic space model.

Upon 3D cubic space is created with each side $2L$, the algorithm samples the space with Δx as the interval between each sample. In other words, the entire 3D cubic space is divided into equal length of columns and rows, where each sampled cube length of Δx, see Fig. 7.

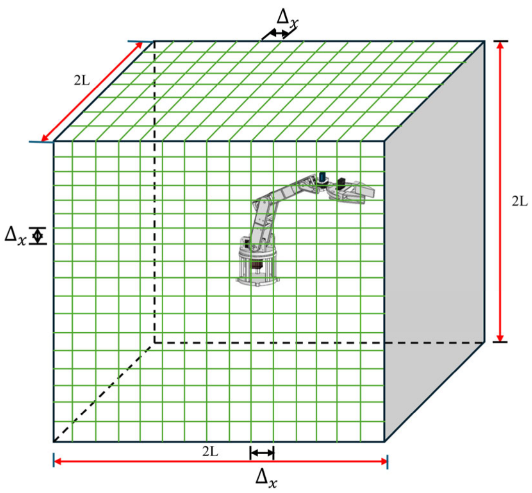


Fig. 7. The sampling of 3D cube space.

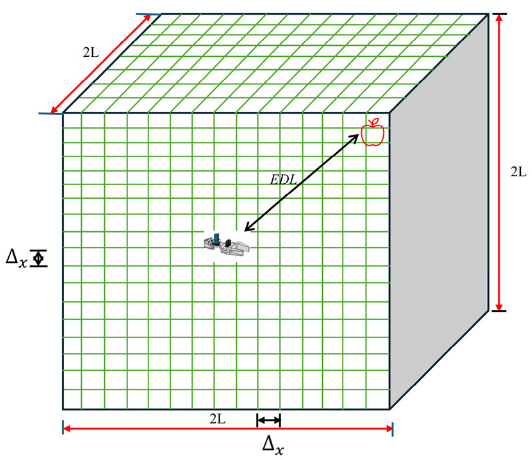


Fig. 8. Diagonal line in 3D cube space.

The object location information is obtained by using position sensor. Once the object location is identified, then a Euclidean Diagonal Line is drawn from the object location to the place where the color sensor exists, see Fig. 8. The color sensor is attached near to robot arm gripper.

The robot arm path is identified with staircase cubes that are close to the *EDL*. In other words, select all the staircase cubes starting from the place where the color sensor exists to the point where the fruit object is located. The path of the robot arm looks like staircase model, see Fig. 9.

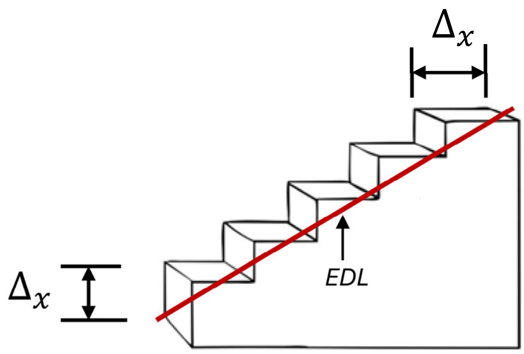


Fig. 9. Staircase model in cube.

The robot arm follows the cube staircases and moves forward. When the robot arm gripper reaches a place, which has at least distance t, the distance from where the robot arm is able to collect the sensor data on the fruit.

If the location of the gripper is (x_1, y_1) and location of fruit is (x_2, y_2) then slope S_l of the *EDL* is.

$$S_l = \frac{y_2 - y_1}{x_2 - x_1} \tag{2}$$

The length of *EDL* is

$$L_{EDL} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{3}$$

The number of steps can be calculated by the following formula.

$$\text{The number of Steps} = \frac{T_r}{I_r} \tag{4}$$

Here, T_r is the total vertical height from the starting point, and I_r is the height of one staircase, see Fig. 10. where,

$$\left.\begin{aligned} T_r &= y_2 - y_1 \\ I_r &= \Delta_x \end{aligned}\right\} \tag{5}$$

The *EDL* angle with the base can be computed as

$$\theta = \sin^{-1}\left(\frac{y_2 - y_1}{L_{EDL}}\right) \tag{6}$$

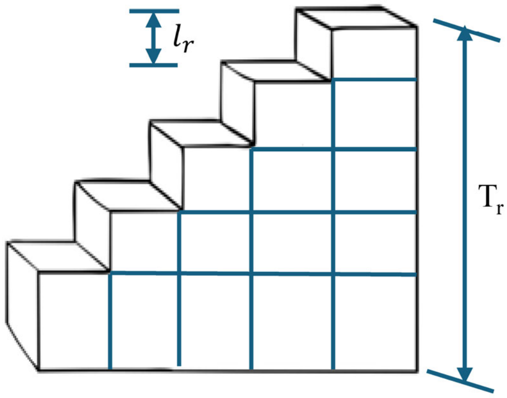


Fig. 10. Staircase heights.

Upon completion of trajectory motion plan, the sensor reaches a place where it can detect the fruit's ripeness in the plant. The proposed model considers the color sensor rather than the image processing applications such as YOLO to identify the fruit's ripeness. The proposed model gets faster response time from the sensor, because the microcontrollers, such as Arduino and Raspberry pi, have low computational capability for these image processing applications. Hence, the proposed structure uses the color sensor to get the fast response time.

The kinematic analysis of the given model is evaluated with respect to the displacement of sensor attached to the robot's gripper. The kinematics of the proposed robot arm model has two types, forward kinematics and inverse kinematics. The forward kinematics focuses on obtaining the gripper's location, with the given different angles of arm joints. In other words, the output of forward kinematics can be computed by taking angles of all the robot arm joints.

There are two ways to obtain forward kinematics, using 3D geometry, and the other method includes matrix transformation functions.

According to the DH convention [44, 45], the modeling of each join movement in the robot arm is represented by 4 × 4 homogeneous transformation matrix.

$$Tj_i = \begin{bmatrix} cos\theta_i & -sin\theta_i cos\rho_i & sin\theta_i sin\rho_i & \sigma_i cos\theta_i \\ sin\theta_i & cos\theta_i cos\rho_i & -cos\theta_i sin\rho_i & \sigma_i sin\theta_i \\ 0 & sin\rho_i & cos\rho_i & q_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{7}$$

where θ_i is the joint angle, ρ_i is the link twist, σ_i is joint offset, q_i is the link length.

The θ_i is the moving variable for a rotational joint. It represents the rotation of the link relative to previous link. The ρ_i shows the structural twist or bend built into the arm's physical structure between two joints. The σ_i represents the thickness of the joint or the length of a sliding link extension. The q_i represent the shortest distance between the two consecutive joint axes. From Eq. (1), the lengths p_1 through p_6 represent the lengths of the joints q_i.

The total transformation of 6-DoF robot arm is the product of all six join motions.

$$T_{total} = Tj_1 \times Tj_2 \times Tj_3 \times Tj_4 \times Tj_5 \times Tj_6$$
$$= \begin{bmatrix} cos\theta_i & -sin\theta_i cos\rho_i & sin\theta_i sin\rho_i & \sigma_i cos\theta_i \\ sin\theta_i & cos\theta_i cos\rho_i & -cos\theta_i sin\rho_i & \sigma_i sin\theta_i \\ 0 & sin\rho_i & cos\rho_i & q_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{8}$$

In the matrix at Eq. (8), the first three columns represent the orientation transformation, whereas the last column represents translation transformation.

A typical 6-Axis Articulated Industrial Robot, such as a FANUC, KUKA, ABB, or the classic PUMA 560, typically uses a six revolute joints design. The first three joints supervise base positioning, while the final three intersecting joints develop a spherical wrist [43]. The DH parameters for such configurations are shown in Table I.

TABLE I. DH CONVENTION FOR 6-AXIS ROBOT ARM

Link	Joint Angle	Link Offset	Link Length	Link Twist	Angle Range
1	θ_1	σ_1	0	90°	−180° to +180° (or up to ± 360°)
2	θ_2	0	q_2	0°	[−85°, +140°]
3	θ_3	0	q_3	90°	−175° to +75° (or up to ± 150°)
4	θ_4	σ_4	0	−90°	−190° to +190° (or up to ± 360°)
5	θ_5	0	0	90°	−115° to +115°
6	θ_6	σ_6	0	0°	−360° to +360°

The σ_1 represents the height of the base column, whereas q_2 shows main lower arm the length. The parameters q_3 and σ_4 configures the upper arm offset and length. The σ_6 represents the length from the wrist center.

The inverse kinematics, in general, be solved by kinematic de-coupling. In other words, the problem of solving inverse kinematics is done with two stages. In the first stage, the lower three joints place the "wrist center", whereas the second stage takes care of "spherical wrist". The joint angle limits of every joint on a 6-axis robot arm are not standard universal constants set by the DH convention. The physical build and safety margins of the actual robot arm model being used define the exact numbers. Typical joint angle ranges for an industrial 6-axis robot are shown in Table I. All standard industrial 6-axis robots follow this as it is widely used mechanical structure.

Math for the 6-DOF robot arm becomes much easier if every stair has the same rise and runs. It can use a stepping pattern instead of recomputing a new target at every step. With the help of kinematic decoupling and some geometric step equation you can solve for the joint angles. Because every step is the same in the sampled cubic space model, it can use the step number (n) to calculate the exact location of any step in the equal step math model. The target position (X_n, Y_n, Z_n) for the robot arm on any step n is:

$$
\begin{aligned}
X_n &= X_0 + n \times U \\
Y_n &= 0 \\
Z_n &= Z_0 + n \times V
\end{aligned}
\tag{9}
$$

where U is the constant horizontal length (run) of each step, Δ_x. The V is the constant vertical height (rise) of each step, which is Δ_x. The n is the current step numbers. Here, $Y_n = 0$, because it assumed that the arm moves are strait forward. The X_0 and Z_0 are the starting coordinates of first step.

It shouldn't try to solve the entire 6-DOF arm at once with inverse kinematics. Split the problem into two parts: Position (Joints 1–3) and Orientation (Joints 4–6). With this configuration the wrist pivot point is actuated by Joints 1–3 instead of the gripper. Your robot must move its stair target backwards by the length of your robot's hand:

$$
\overrightarrow{I_b}\ \begin{bmatrix} X_n \\ Y_n \\ Y_n \end{bmatrix} - d_6\,\overrightarrow{S_z}
\tag{10}
$$

where $\overrightarrow{S_z}$ is the direction, the arm is pointing at the step.

Now it should point the arm toward the step. Next, use some geometry to solve for the first three angles with the wrist center coordinates. Joint 1 of the 6-DOF arm aligns itself with the stair. Links 1 and 2 with the wrist center form a triangle for Joints 2 and 3. Calculate the bending angles using the Law of Cosines based on the robot arm segment lengths. Finally to finish the orientation, it has the wrist cancel out the first three joints' angles and have your gripper finish parallel with the equal height steps. Pre-Multiply the desired orientation matrix by the inverse rotation of Joints 1–3. Use basic trigonometry to solve for θ_4, θ_5, and θ_6 from the remaining members in the matrix.

The EDL led staircase path shows an approximated guided path from the present location to a place close by to fruit. The proposed EDL guided trajectory path plan model is the macro-level path plan, and it brings few benefits, such as low energy consumption, and low latency in reaching predetermined location because the EDL shows the shortest distance between current location and intended location. At micro-level, proposed robot arm model uses 6-axis DH convention kinematics model, while gripper reaches the destination with different DH parameters. However, the DH parameter values for the proposed model primarily depends on two factors, EDL slope, and the EDL length.

The 6-DOF robot arm goal position (X_n, Y_n, Z_n) for fruit ripen evaluation is gathered from position sensor data. The EDL is plotted from the target location to the current location, followed by the sampling process to get the cubic space model. With the staircase model, the robot arm follows EDL in accordance with DH convention. The microcontroller produces servo motor drive signals using a method called Pulse Width Modulation (PWM). It creates a repeating electrical pulse by rapidly switching a digital pin ON and OFF. How long the pulse stays ON tells the servo motor exactly what angle to turn to. The high and low voltage pattern is emitted from the microcontroller through a specific PWM output pin.

IV. RESULTS AND DISCUSSION

The simulation work is conducted by conducting experiments on the fruit harvesting process to identify whether the fruit is ripened or in raw state. To conduct this experiment, we have used Arduino Uno microcontroller. The Arduino Uno is ATmega328P. The clock speed is 16 MHz, whereas 2 KB of internal memory, 32 KB of external memory, and 1 KB of Electrically Erasable Programmable Read-Only Memory (EEPROM). The number of digital Input-Output pins are 14, and 6 analog inputs exist. The color sensor chosen for the harvesting process is TCS3200 Color Sensor Module compatible with raspberry pi and Arduino, see Fig. 11. The input voltage for the sensor is 3.3v to 5v. The response time for the sensor typically be 2 milliseconds. The Arduino code is written to identify the RGB color values from the sensor. In the experiments, it calculated RGB values for both red and green color objects, as generally the fruit is considered ripen when the fruit is in red color and it is considered raw state when the fruit is in green color.

Fig. 11. TCS3200 color sensor.

For each object, the RGB color values are taken and plotted the graphs. The object is kept at various distances of 1 cm, 3 cm, 5 cm, and 7 cm from the color sensor. Figs. 12(a)–(d) show plots for the RGB values of red color object with the distances 1 cm, 3 cm, 5 cm, and 7 cm, respectively. From the plot, it shows that the R value in RGB color model is low, which confirms resultant color is red. The next experiment is calculated to detect the green color object. Figs. 13(a)–(d) show the plots of RGB color values for green color object with distances 1 cm, 3 cm, 5 cm, and 7 cm respectively. However, some discrepancies occurred in the experiments with distances between 5 cm and 7 cm, because the higher distances may give a chance of errors. Moving a color sensor further away from an object triggers color reading errors because the light bouncing back develops weaker and mixes with surrounding area light. When you pull the sensor back, three main things go wrong. The first one is that light signal gets weaker, and the sensor cannot read the weak light accurately. The second one is that the area light mixes with extra light, such as ambient light leakage, color bleeding, and finally it mixes with the object's real color and tricks the sensor. The third one is that the sensor view area gets too big, which brings together the problems such as color blending, spreading the sensor light beams, increases the background pollution, and finally the sensor averages all together cause the sensor output errors. However, ff the color sensors are taken from industrial standards, then the correctness of object's color is more accurate for longer distances values too.

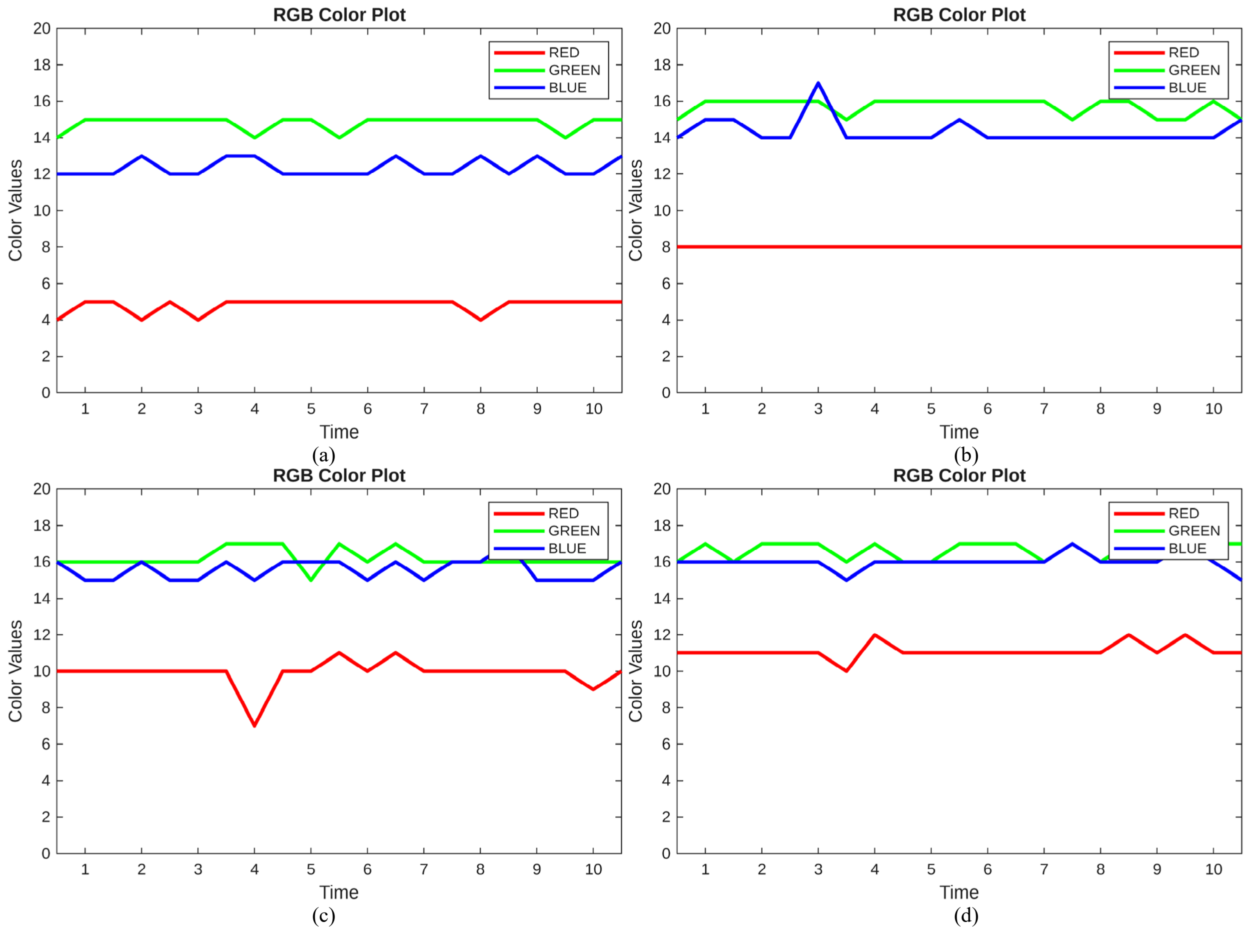
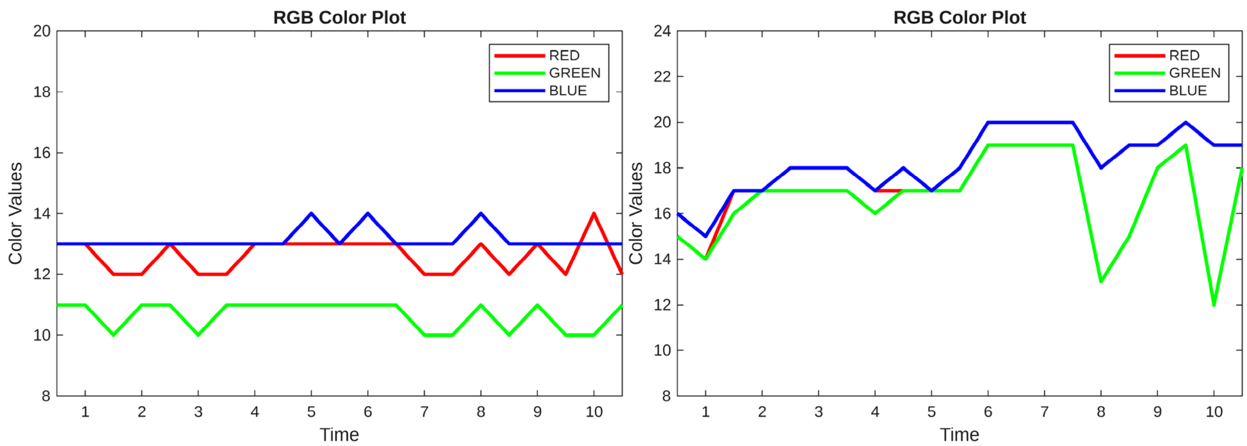
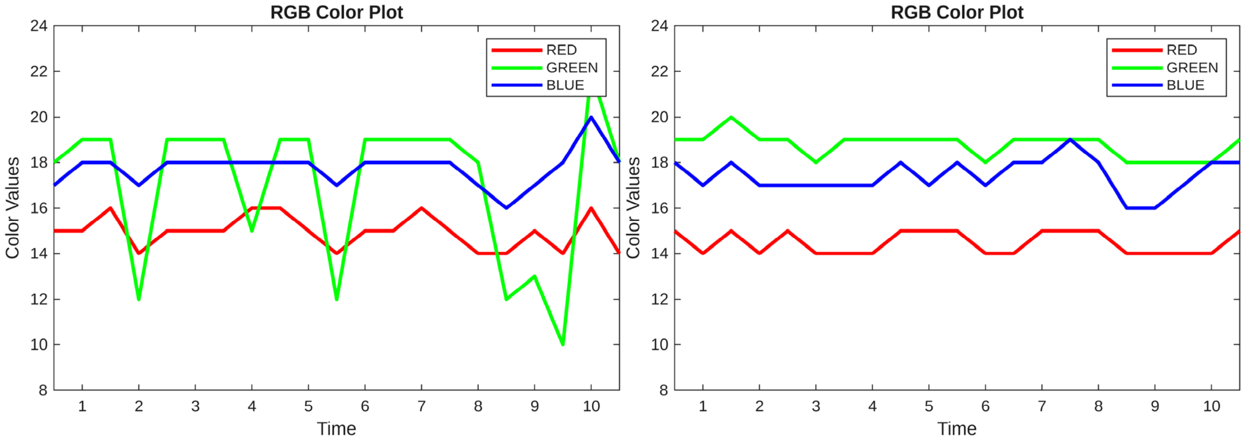


Fig. 12. RGB color values for red color. (a) 1 cm; (b) 3 cm; (c) 5 cm; (d) 7 cm.



(a)

(b)



(c) (d)

Fig. 13. RGB color values for green color. (a) 1 cm; (b) 3 cm; (c) 5 cm; (d) 7 cm.

Simulation work is done using MATLAB on analyzing the forward kinematics of the 6-DOF robot arm, see Table II. In this experiment, the input is taken as different angles of six joints in the robot arm. Here the θ_1, θ_2, θ_3, θ_4, θ_5, and θ_6 represent the angles of Joints 1–6, respectively. The location of the gripper is computed using the transformation matrix with the model provided in Eq. (8).

TABLE II. 6-DOF FORWARD KINEMATICS

Input Angles of 6-DOF Robot Arm						Gripper Location		
θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	x	y	z
0	45	−45	0	90	0	0.4828	−0.2	0.7828
0	45	−45	30	90	0	0.4962	−0.2	0.7328
0	45	−45	45	90	0	0.5121	−0.2	0.7121
0	45	−45	60	90	0	0.5328	−0.2	0.6962
0	45	−45	90	90	0	0.5828	−0.2	0.6828
0	45	−45	0	30	0	0.5328	−0.2866	0.7828
0	45	−45	0	45	0	0.5121	−0.2707	0.7828
0	45	−45	0	60	0	0.4962	−0.25	0.7828
0	45	−45	45	30	30	0.5475	−0.2866	0.7475
0	45	−45	45	45	30	0.5328	−0.2707	0.7328
0	45	−45	45	45	90	0.5328	−0.2707	0.7328
0	45	−45	45	60	90	0.5216	−0.25	0.7216

The link offset, link length, and link twist values considered during the simulation work is shown in Table III.

TABLE III. TWIST ANGLE, OFFSET, LINK LENGTH

Joint no.	ρ (radians)	σ (meters)	q (meters)
1	$\pi/2$	0.5	0
2	0	0	0.3
3	0	0	0.4
4	$\pi/2$	0.2	0
5	$-\pi/2$	0	0
6	0	0.1	0

The MATLAB's DH analysis results are considered to be correct if and only if the final numerical pose matrix is correct.

YOLO based methods are intelligent but expensive in terms of cost and high-end GPU. Color sensor-based detection approach is inexpensive but has certain drawbacks. Color sensor should always be near to the object to get precise value. It typically detects only bright primary colors (Red, Green, Blue). Table IV compares sensor-based detection approach and YOLO vision-based approach.

TABLE IV. COMPARISON OF COLOR SENSOR AND YOLO

Performance Parameters	Color Sensor Based Detection	YOLO Vision Approach
Response time	Extremely fast	Slower
Cost	Very Cheap	Expensive
Accuracy	Low	High
Processor	Tiny Microcontrollers	Computers, Jetson Nano, or PC

V. CONCLUSIONS

Robotics contribution in agricultural forms is significant to keep in mind the importance of modern agriculture forming techniques in the present society. The 6-DOF robot arm is useful for many indoor forming, because of its accuracy and flexibility. The paper presented a prototype design with various components, such as 6-DOF arm, sensors, microcontroller development board, and a gripper. At a macrolevel, a three-dimensional unit step trajectory motion plan and related analysis for the robot arm have been presented. In addition, the paper described the parameters of 6-DOF robot arm's kinematic analysis for the proposed methodology. Experimental tasks are conducted to verify whether the fruit is ripened or still in the raw form, and the results are presented. Even though the proposed methodology has fast response time, it has some limitations on the accuracy of detecting the color of the fruit when it has different sunlight effects in outdoor environment. As a future work, it will be explored to study different approaches of getting higher accuracy in detecting fruit color in outdoor environment, without losing the characteristics of fast response time by using sensors.

Ethics Approval

The ethical approval has been obtained for this article from College Research Committee, University of Buraimi, Oman.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

SD and AAK: Conceptualization, Methodology, Algorithm Designs. MKS, GR, NKSL, AHAA: Data Collection, Formal Analysis, Writing-Review and Editing. All authors had approved the final version.

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