Wi-Fi Module based Vegetable Plucking Robot

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Abstract - To overcome labor shortages and meet the increasing demand for high-quality yield, the agriculture field is moving towards technological solutions. The Wi-Fi module controlled vegetable plucking robot is a modern technology that can effectively automate the vegetable harvesting process. The proposed robot contains a Wi-Fi module which enables remote control from a computer or smartphone. It makes use of sensors and advanced algorithms to identify the ideal time for harvesting and to pluck vegetables gently to avoid hurting the plants. This technology has the possibilities to improve crop quality, enhance yield, and reduce labor expenditure for farmers. This Wi-Fi module controlled vegetable plucking robot set out as an outstanding example of how technology can address the current challenges in modern agriculture.

***Key Words*:** *Wi-Fi module, sensors*

1. INTRODUCTION

The Wi-Fi module controlled vegetable plucking robot is a cutting-edge invention that is revolutionizing agriculture. Farmers are implementing new technologies to increase their production as a result of a lack of labor and an increase in the demand for food of high quality. By automating the vegetable harvesting procedure, this robotic gadget not only improves crop quality but also saves time and labor. The robot has a Wi-Fi module that enables farmers to remotely control it using their smartphones or computers from any location in the world. By giving farmers more flexibility and control over their farming operations, this technology enables them to manage their crops more effectively. The sophisticated Wi-Fi module-controlled vegetable plucking robot employs cutting-edge sensors and algorithms to identify the best moment for harvest and gently pluck the vegetables from the plants to prevent plant damage. By ensuring that the crops are harvested at the proper time, this method increases crop quality and yields. The robot can also distinguish between ripe and unripe vegetables, leaving the latter on the plant for later harvest and reducing crop waste.

The Wi-Fi module controlled vegetable harvesting robot has the ability to completely change the way agriculture is carried out. Farmers can greatly save labor expenditures by using it instead of manual harvesting. Additionally, the robot can operate around the clock, guaranteeing that crops are gathered on schedule even after-hours. With the use of this technology, farmers may operate more productively, save time, and manage their operations more effectively. An excellent illustration of how technology may be used to address the issues facing modern agriculture is the Wi-Fi module controlled vegetable plucking robot.

2. Literature survey

G. Kondo et al [1] proposed an end-effector to pick tomatoes without causing any damage, a manipulator with seven degrees of freedom, and a traveling device that makes up a tomato harvesting robot. The vision sensor must enable the robot to recognize the color and location of items. Additionally, it needs to recognize where barriers like leaves and stems are located. The tomato fruit cluster often contains numerous fruits that are next to another fruit. Sometimes the two finger end-effector damages stems or other fruits. As a result, the suction pad on the harvesting end effector was used to separate the objective fruit from the other fruits. Since the tomato peduncle contains a joint, picking the fruit by bending the wrist instead of cutting it was used. The manipulator was controlled to have a large straight moving distance from the end-effector and to be easily manipulable.

Gotou et al [2] has explained in his paper that a 3D vision sensor was constructed and mounted to the end of the manipulator to create a multifunctional robot for the production of tomatoes. In order to scan the object, the sensor released red and infrared laser beams. Experiments with image recognition for plant training and fruit harvesting have been conducted. The location of the red ripe tomato and the other objects could be identified in the hit harvesting operation. It was possible to identify the tomato plant and the white pole that served as a prop for the plant training activity. These tomato manufacturing activities would be a good fit for the 3D vision sensor.

Yang et al [3] describes a technique for automatically harvesting mature tomato fruit clusters on complex-structured tomato plants that are cluttered and obscured by other plants in a tomato greenhouse. The vision sensor is a color stereo vision camera (PGR BumbleBee2). The suggested technique does 3D reconstruction using data gathered by the stereo camera to build a 3D processing environment. In order to separate the mature fruits from the leaves, stalks, background, and noise, the Color Layer Growing (CLG) method is introduced. Then, depth segmentation can be used to locate the desired fruit clusters. The strategy was supported by the experimental findings, which were gathered from a tomato greenhouse. We incorporated severe self and stereo occlusion in our studies, which was not done in the earlier research.

Kundu et al [4] has explained that the Solanaceae family of plants, which includes the tomato, is widely cultivated. The genetic purity of cultivars is crucial to farmers, plant breeders, seed companies, as well as regulatory organizations, in agriculture. Different tomato cultivars and species are categorized using genetic and physical traits. However, it is difficult to categorize tomatoes due to the wide differences in their fruit and leaf morphologies. This study used image processing approaches to enhance the binarized pictures that came before the most important step of shape-based feature extraction on tomato leaves and fruits. In order to develop a prototype model for tomato leaf recognition, several morphological features are collected and examined. Prior to Principal Component Analysis, features are modified for dimension reduction in order to improve feature visibility.

Hongpeng et al [5] has explained that it is planned to employ a robotic system to harvest tomatoes in greenhouses. The core technology of the harvesting robotic system is the accurate detection of ripe tomatoes against a complicated background. The color characteristic of ripe tomatoes is used in this piece. By employing the L*a*b* color space and K-means clustering, the ripe tomato is divided into sections. The mathematical morphology method is used to de-noise and handle tomato overlapping and sheltering conditions in order to obtain a single integrity ripened tomato. The efficiency of the suggested strategy is demonstrated by experimental data.

Cakir et al [6] proposed that in order to create software for an automatic orange collector robot system, a strategy is proposed in this paper to identify orange fruits on trees using image processing techniques. Computer vision-based fruit detection has significant drawbacks. The biggest issue is the environment's inconsistent external lighting. The obstruction of fruits by leaves, branches, and other fruits is a further issue. These issues are looked at in the proposed methodology as well.

Akin et al [7] proposed in this work, a technique is put forth for locating pomegranate fruits on trees and determining the total quantity of pomegranates using close-up camera photos received from stations set up the groves. Given that the pomegranate has a prominent red hue, a color-based technique is used to identify the fruits on the tree. Color alone is insufficient to create a pomegranate detection algorithm that is reliable enough. Tree branches and leaves typically have more straight or pointed shapes than do pomegranates, which typically have spherical shapes. Finding fruit can be as simple as looking for rounded items. There are some issues with the machine-based fruit segmentation (lighting and occlusion). These issues are looked at in the proposed methodology as well.

Jian Song et al [8] has explained that for a robot that picks eggplants, an automatic threshold-based target recognition method is suggested in order to increase the vision systems intelligence and responsiveness. Through experimentation and statistical analysis of the color characteristics of the eggplant fruit in growing environments and their surroundings, it is concluded that the EXG color factor is the most advantageous for segmenting images of eggplant fruit. EXG gray scale images are segmented using an automatic threshold method. The initial threshold is estimated using the mean of the image's gray scales, and iterations are repeated until a satisfying outcome is obtained. Such features as the contour, area, circumscribed rectangle, and cut-out point of the fruit target are extracted in accordance with the specifications for the vision system of the fruit-and-vegetable picking robot.

Gejima et al [9] has explained that this research discusses the use of color image processing to assess tomato quality maturity. The RGB and L*a*b* color systems were employed in the image analysis. The analysis revealed that the G (36) pixel count had the highest association to tomato ripeness. However, the radical regression curve of G was not as accurate as the average value of a* of the tomato upper surface as a measure of maturity of fruit.

GuoFeng et al [10] proposed that it is suggested to utilize a machine vision system for automatic, quick fruit sorting. With the help of an Ohta-color-space based thresholding method, the fruit area was first separated from the background of the image. Noise was then removed using the blob approach, and the fruit contour was detected using a spline-interpolation based algorithm. Fruit color ratio, which was determined using the HSI color space, was chosen as a categorization characteristic in the sorting procedure. The traditional Bayes classifier, whose parameters were determined via a research module, was used to sort the fruit. Using Crystal Fuji apples as the test subject, this system produced average sorting accuracy of 90%.

D Amato et al [11] proposed that the color is a criterion used in fruit packing businesses to assess fruit quality, maturity, healthiness, etc. The color of an apple also identifies its class or variety. Today, the differentiation between the various apple characteristics is made using empirical metrics suggested by professionals. This research presents a mechanical-digital system for real-time fruit color classification and capture. It is intended to be integrated into an existing fruit delivery system. A very large number of lines may be processed by a single commercial PC thanks to the tracking algorithms that were created utilizing graphics cards. The solution may simulate human criteria for classifying fruits. The system produces output showing the quality, which is utilized to distribute the fruit bundles, based on photos acquired from the transport line.

J. Hemming et al [12] has explained that the outcomes of creating a robot to pick sweet peppers in greenhouses are discussed in this study. The manipulator, control electronics, and computers are situated on the first floor. On the greenhouse rail system, the connected modules may be moved in between the rows of crops. Module heights may be changed to correspond to crop height. The three dimensional (3D) data and color pictures were calibrated and registered. Ripe fruits and impediments are located in 3D using machine vision software. Different methods have been explored for fruit detection. One method is to start the fruit detecting process by merely looking for blobs of red color. An additional choice is to carry out fruit localization in two successive phases. The first regions of interest in the RGB picture that are thought to contain the target fruits are chosen.

J. Bontsema et al [13] has explained a growing area of study that combines characteristics of machine intelligence and machine vision is automated or robotic assisted collecting. Image processing has demonstrated to be an effective tool for analysis in a variety of performance domains, particularly agricultural applications. The robot, which would desire to pick up fruit and type different fruits and veggies, received the majority of it. Computer vision applications that need almost human levels of recognition may potentially face significant challenges from identification and categorization. The suggested strategy takes a variety of fruits into account. There has been a lot of study done on this topic recently, either utilizing straightforward methods like color-based grouping in computer vision or additional sensors like LWIR, hyperspectral, or 3D.

E. Van Henten et al [14] proposed that the idea of an autonomous robot for greenhouse cucumber picking is presented. The operating environment of the robot and the harvesting logistics are described. 4 harvesting robots and 1 docking station are reportedly needed during the busiest season for a 2 hectare Dutch nursery. The fundamental condition is that single harvest processes can only last ten seconds. The study then concentrates on the various hardware and software parts of the robot. The autonomous vehicle, the manipulator, the end effector, the two computer vision systems for the detection and 3D imaging of fruit and surroundings, and last but not least, a control strategy that provides collision-free movements for the manipulator during harvesting, are among them. There are seven degrees of freedom for the manipulator. The ripeness of the cucumbers is assessed using geometric models.

S. Mehta et al [15] has explained the primary contributions of this study are the construction of a vision-based estimate and control system for robotic fruit harvesting and a thorough stability analysis to ensure the effectiveness of the closed loop system. The huge field-of-view of a fixed camera and the precision of a camera in-hand enhance the cooperative visual servo controller that is being described (CiH). Using a monocular camera and a computationally cheap perspective transformation based range estimate algorithm, the location of the 3D fruit is determined in order to enable real-time manipulator control. A rotation controller is created to position the robot such that CiH linked to the end-effector can see the target fruit chosen by the fixed camera. The provided pursuit guidance based hybrid translation controller may then be used to servo the end-effector to the desired fruit location. Global exponential control of the end-effector is guaranteed by a stability analysis based on Lyapunov equations. While the performance is assessed using an artificial citrus tree and a seven degrees of freedom kinematically redundant manipulator, numerical simulations are used to confirm the viability of the designed controller.

3. CONCLUSIONS

In conclusion, the Wi-Fi module operated vegetable plucking robot is a creative and intriguing technological advancement that has the potential to change the agricultural sector. This tool can efficiently harvest crops by combining wireless communication with robotics, boosting productivity and lowering the demand for physical labor. Although the technology is still in its infancy, it has already shown a range of outstanding abilities, and farmers who have tested it have given it good reviews. The Wi-Fi module operated vegetable plucking robot has the potential to transform the agricultural sector and help create a more effective and sustainable food production system with further development and improvement.

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