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AGRICULTURAL FRUIT HARVESTING ROBOT: AN OVERVIEW OF DIGITAL AGRICULTURE

N.B. Bharad* and B. M. Khanpara

Department of Farm Machinery and Power Engineering, College of Agricultural Engineering and Technology, Junagadh Agricultural University, Junagadh – 362 001, Gujarat, India

*Corresponding author's Email ID:nirajbharadbn@gmail.com

ABSTRACT

The integration of robotics into agriculture has ushered in a transformative era, offering innovative solutions to longstanding challenges such as labor shortages, rising production costs, and the need for increased efficiency. Among these advancements, agricultural fruit harvesting robots have emerged as a pivotal development, poised to revolutionize traditional farming practices. This paper presents a comprehensive overview of autonomous fruit harvesting robots, impact on agricultural practices. The Agricultural Fruit Harvesting Robot (AFHR) represents a significant milestone in modern agriculture, equipped with state-of-the-art sensors, actuators, and machine learning algorithms. Its capabilities encompass the identification of ripe fruits, delicate manipulation, and efficient harvesting from trees. The AFHR's design prioritizes versatility, enabling adaptation to various fruit types, shapes, sizes, and orchard configurations, ensuring broad applicability across diverse agricultural landscapes. Key technological features, including computer vision and machine learning algorithms, empower the AFHR to discern fruit maturity levels, optimizing harvesting timing to maximize yield and minimize waste. Autonomous navigation systems facilitate efficient traversal of orchards while avoiding obstacles, reducing labor requirements and minimizing plant damage. The integration of soft grippers on robotic arms ensures gentle fruit handling, mitigating bruising and damage during harvesting. Autonomous fruit harvesting robots offer a promising solution to address labor shortages, enhance efficiency, and improve the sustainability of fruit production systems. Continued advancements in technology are anticipated to further refine the capabilities and foster widespread adoption of these robots in agricultural practices. The AFHR stands at the forefront of agricultural innovation, poised to redefine the future of fruit harvesting, fostering increased efficiency, sustainability, and profitability in the agricultural sector.

Keywords: Robotics, computer vision, sensors, algorithms, robotic arms.

Introduction

In the 20th century, developed countries witnessed a dramatic decline in the agricultural workforce, shrinking by 80 times [1]. Nonetheless, manual labor remains a significant cost factor, constituting 40% of the total production expenses for vegetables, fruits, and cereals [2]. The evolution of modern agriculture has spurred the adoption of robotic and intelligent machinery, driven by several key factors. Firstly, the escalating costs and diminishing availability of skilled labor pose significant challenges to the industry. Secondly, ensuring food safety has become paramount, necessitating the deployment of reliable robotic systems to minimize contamination risks [3]. Thirdly, the imperative of sustainable agriculture, balancing food production with environmental preservation, underscores the need for robotic technologies to enhance productivity while minimizing costs [4].

Horticulture, known for its labor-intensive nature, relies heavily on manual labor, with automation currently only accounting for 15% of operations. This manual approach extends to fruit harvesting, contributing significantly to crop shortages, which can reach a staggering 50%.Moreover, the urbanization trend further complicates the recruitment of seasonal workers for harvests [5].It's evident that widespread adoption of robotics could revolutionize horticulture, enhancing productivity, alleviating manual labor burdens, and ultimately reducing crop shortages.

In recent years, the agriculture industry has witnessed a significant shift towards automation and robotics to address challenges such as labor shortages, increasing production demands, and improving efficiency [6]. Fruit harvesting, in particular, has emerged as a sector ripe for technological innovation. With the advent of intelligent robotics, farmers can now harness advanced automation solutions to streamline the harvesting process, optimize yield, and ensure the quality of produce. The examination of robotic harvesting systems reveals two primary classifications: fully integrated systems and subsystems dedicated to harvesting tasks. These subsystems encompass various functionalities, including vision [7], gripper technology [8], and control mechanisms [9].

In the early 1960s, [10] explored the idea of an automatic harvester, envisioning a system utilizing robotic technology for fruit picking. Their proposal involved a robotic arm equipped with a manipulator to reach and detach fruit from trees, guided by a machine vision system for detecting the fruit. However, the agricultural setting posed significant challenges to fruit detection, given the unstructured environment, sensor limitations, and the need for robust methodologies. Consequently, the development of reliable solutions remains a pressing issue, prompting ongoing research efforts aimed at addressing these multifaceted challenges. This review paper aims to outline existing techniques and ongoing research endeavors in fruit harvesting.

Mechanical harvester

Since the early 1960s, researchers have delved into mechanical harvesting techniques[11]. Coppock proved that it was possible to shake a citrus tree mechanically to extract fruit from its branches without damaging the tree itself, and so claimed that citrus fruit could be harvested mechanically. Pre-harvest abscission spray was also suggested to loosen the fruits on the tree and lessen the physical harm to the tree. Furthermore, to enhance the design of mechanical harvesters, the biological and physical properties of the fruit were also studied by [12]**.**

Coppock and Jutras [13] constituted an early version of Adrain and Fridley's inertia-based limb shaker. The mechanism produced the shacking action by rotating an eccentric weight of approximately 38.5 kg once the shaker was fixed to the tree limb. The fruit will be picked using the auger-shaped spindle-style picking tool without sustaining too much harm. The clamping mechanism notably caused considerable damage to the tree's bark. The primary obstacle to implementing this idea in a workable device is the inability to arrange the apparatus in a way that allows it to continuously and non-selectively remove every fruit from the tree canopy.

Jutras and Patterson [14] examined the efficacy of an oscillating air blast apparatus for harvesting citrus fruit. Their findings revealed that the rate of oscillation significantly influenced fruit removal, with higher oscillation rates resulting in greater removal percentages. The research suggested that employing the oscillating air blast method could facilitate citrus harvesting, yielding removal rates ranging from 40% to 95.6%. Interestingly, while the oscillating air blast method proved effective for fruit removal, it also presented challenges in post-harvest handling. Specifically, it was observed that utilizing this method led to increased post-harvest decay when compared to traditional hand picking or automatic robotic picking techniques.

Coppock [15] studied a mechanical method for harvesting trees involved employing fixed stroke, inertia, and direct impact on tree limbs to shake them. A system comprising two catching frames, each equipped with a tree shaker, was capable of harvesting 10 trees per hour with a 3-person crew. The efficiency of fruit removal using these systems ranged from 90 to 95%. However, several challenges arose from this method, including fruit damage caused by falling foliage, lower removal rates during the early and middle stages of the harvesting season, and the unintentional removal of both large and small immature fruits.

Wilson *et al*. [16] examined in their study the efficacy of an air shaker combined with pre-application of an abscission agent on FMC-3. This approach involved integrating the use of the abscission agent into the pre-harvest process, specifically as part of the air shaker harvesting method. The abscission agent was administered using air carrier sprayers, while trees were subjected to shaking via an experimental air shaker equipped with a conical scanning air delivery system. The harvesting rate achieved was 1.5 acres (0.6 ha) per hour. Results showed that fruit removal rates ranged from 97% to 99%.

Futch and Roka [17] conducted a study on two types of canopy shakers designed for continuous operation: one was a self-propelled unit, while the other was a tractor-drawn unit. Following the harvest, manual labor was required to gather the fruits. Key performance factors included the shaking frequency and stroke of the machinery. These harvesters were capable of harvesting between 100 and 200 trees per hour. Research carried out by the Florida Department of Citrus, the University of Florida, and private enterprises indicated that these systems could reduce harvesting costs by 20 to 40 cents per box.

Torregrosa *et al*. [18] conducted researchers in Spain to evaluated the efficacy of a tractor-mounted trunk shaker compared to a hand-held shaker across various orange and mandarin varieties. The results showed that the tractor-mounted shaker outperformed the hand-held shaker, achieving a detachment rate of 72% compared to 57% with the hand-held method. However, it was observed that fruits picked from the ground during testing exhibited a notable incidence of bruising. Moreover, there were concerns regarding defoliation, particularly at higher shaking frequencies, and bark damage during the months of May and June.

Automatic harvester

The traditional method of harvesting fruits and vegetables for the fresh market is labor-intensive, requiring a shift towards automated processes to enhance efficiency and reduce dependency on manual labor. Despite advancements in agricultural robotics, a significant portion of fruits and vegetables are still hand-picked annually in both open fields and greenhouses. This reliance on manual labor not only results in high costs but also poses challenges in finding skilled workers willing to perform repetitive tasks in challenging field conditions. To justify the cost-effectiveness of robotic harvesting, it's crucial to maximize fruit yield to offset automation expenses. However, achieving this goal becomes increasingly difficult due to the necessity of growing plants at higher densities, which presents challenges for autonomous robots in detecting, localizing, and harvesting fruits simultaneously.

Van Henten *et al*. [19] introduced an innovative approach to cucumber harvesting in greenhouses, employing a computer vision-based autonomous robot. This robotic system utilizes two cameras equipped with distinct filters to detect cucumbers within the greenhouse environment. Impressively, the computer vision system boasts a detection rate exceeding 95% for locating cucumbers. Furthermore, employing geometric models, the system assesses the ripeness of the identified cucumbers. Field trials subsequently validated the robot's capability to harvest cucumbers autonomously, achieving an 80% success rate without the need for human intervention. Notably, the robot demonstrated efficiency, averaging 45 seconds to harvest each cucumber.

Baeten *et al*. [20] elucidated the development and operational principles of an Autonomous Fruit Picking Machine (AFPM) designed specifically for robotic apple harvesting. Utilizing dual-level sensors, the AFPM orchestrates precise positioning of the robotic platform throughout the picking process. Experimental findings showcase an impressive detection and harvesting rate of approximately 80% for apples within a diameter range spanning from 6 cm to 11 cm. The primary objective remains the reduction of the picking cycle duration from an average of 9 seconds to approximately 5 seconds, or less. Achieving this target aims to elevate the productivity of the AFPM to a level comparable to the workload of approximately 6 manual labourers, rendering the machine economically feasible.

Tanigaki *et al*. [21] introduced a cherry-harvesting robot designed for trial purposes, which underwent basic experimentation. Comprised of essential components including a 3-D vision sensor, an end effector, a computer, and a traveling device, this robot aimed to optimize cherry-picking processes. The 3-D vision sensor utilized red and infrared laser diodes to concurrently scan the objects. Through image processing, the sensor identified the positions of both fruits and obstacles, facilitating the determination of the end effector's trajectory.

Hayashi *et al*. [22] developed a robotic system specifically for harvesting strawberries grown in elevated substrate culture. This innovative robot featured various components including a cylindrical manipulator, end effect or, machine vision unit, storage unit, and traveling mechanism. The machine vision unit was a notable aspect of the robot, comprising five light sources, each equipped with 120 LED chips, and three aligned CCD cameras. This setup enabled the system to detect fruit peduncles with a commendable 60% accuracy rate. During harvesting tests conducted on strawberries at over 80% maturity, the system demonstrated a 41.3% success rate when utilizing suction-assisted picking, and a slightly lower rate of 34.9% without suction assistance. Impressively, the harvesting time per fruit, including transfer, averaged 11.5 seconds. Moreover, the system's execution time was estimated to be 2.5-3 times quicker than manual harvesting methods. This robotic solution showcases promising advancements in agricultural automation, offering potential benefits such as increased efficiency and reduced labor demands in strawberry cultivation.

De-An *et al*. [23] created a robotic apple harvesting tool with a manipulator, end-effector, and image-based vision servo control system. The pneumatically operated gripper on the spoon-shaped end-effector was created to satisfy the demands of apple picking. With the aid of a vision-based module, the harvesting robot carried out its work autonomously. Visual C++ 6.0 was chosen as the programming development tool for the host computer. The effectiveness of the device was evaluated through 100 picking tests conducted at 10 different positions. Results indicated a 77% success rate in apple harvesting, with an average time of approximately 15 seconds per apple. These findings suggest that the prototype machine and control system hold promise for outdoor picking operations.

Hemming *et al*. [24] devised a robotic system designed specifically for harvesting sweet-peppers within greenhouse environments. In Europe, the annual yield of sweet pepper fruit is estimated to be around 1.9 million tons. The robot's manipulator controller utilizes the xPC Target real-time software environment developed by MathWorks (located in Natick, USA), operating on a dedicated x86-based PC. Reports indicate that the automated harvesting process requires an average of 6 seconds per fruit. However, current technology has only achieved a success rate of 33%, with an average picking time of 94 seconds per fruit. During initial testing phases, 97% of the fruits (189 out of 194) were successfully detected, 86% (167 fruits) were reachable, and 79% (154 fruits) were successfully picked.

Yasukawa *et al*. [25] introduced a novel approach to automate tomato fruit harvesting through the integration of an infrared imaging system and a fruit picking technique utilizing specular reflection. Their research concentrated on identifying distinctive features of tomatoes and devised a two-wavelength 3D vision sensor for this purpose. This sensor operates by emitting near-infrared and red laser beams coaxially and capturing the reflected light on a Position Sensitive Device (PSD) with the aid of a lens to measure distances accurately. The detection of fruits within the harvesting chamber relies on pinpointing the center of the fruit, which exhibits strong specular reflection in the infrared image. Upon evaluation with real-world environmental images, the system achieved an impressive correct answer rate of 88.1%.

Feng *et al*. [26] engineered a harvesting robot comprising a stereo visual unit, an end-effector manipulator, a fruit collector, and a railed vehicle. They utilized the R-G colour model to enhance the contrast between the target fruit and the background by analysing the colour features of images captured by the camera. For fruit identification within a cluster, they employed the CogPMAlignTool from the Cognex VisionPro image processing classlib. Following the development, field testing ensued, and the outcomes were meticulously analysed. The robot demonstrated a commendable 83% success rate in harvesting. However, on average, each successful harvest required 1.4 attempts. Furthermore, a single successful harvesting cycle took 8 seconds, exclusive of the time spent on movement.

Altaheri *et al*. [27] suggested a productive architecture for machine vision that will help robots harvest dates. A stream of pictures (frames) from an RGB video camera in a date orchard is the input used by the framework. Comprising three distinct classification models, it aims to swiftly categorize date fruit images in real-time based on their type, maturity level, and whether they are ready for harvesting. The classification models for type and maturity employ a technique known as transfer learning, leveraging pre-trained convolutional neural network (CNN) models and fine-tuning them to suit the specific task at hand. The study delves into the efficacy of two prominent CNN architectures, namely AlexNet [28] and VGGNet [29], which vary in their size and depth. They generated a dataset of 8000 photos of five different date types at varying stages of pre-maturity and maturity in order to develop a robust vision system. The proposed date fruit classification models achieve 99.01%, 97.25%, and 98.59% with classification times of 20.6, 20.7, and 35.9 msec for the type, maturity, and harvesting decision classification tasks, respectively.

Yu *et al*. [30] introduced the Mask Region Convolutional Neural Network (Mask-RCNN) as a solution to enhance the effectiveness of machine vision in detecting fruits, particularly for a strawberry harvesting robot. Their approach involved training the Region Proposal Network (RPN) in an end-to-end fashion to generate region proposals for each feature map. Upon evaluation using 100 test images, the fruit detection performance exhibited promising results. Specifically, the average precision rate stood at 95.78%, with a recall rate of 95.41%. Moreover, the mean intersection over union (MIoU) rate for instance segmentation reached 89.85%, indicative of the model's robustness in delineating fruit instances. Additionally, the prediction accuracy for ripe fruit picking points, as demonstrated by 573 instances, showcased a minimal average error of ±1.2 mm, underscoring the network's precision in practical applications.

Xiong *et al*. [31] proposed an innovative obstacle-separation algorithm to enhance strawberry harvesting by enabling the robot to collect clustered strawberries. Equipped with a Hokuyo LIDAR for navigation and an RGB-D camera for detection, the system adeptly manoeuvres through foliage and obstacles using its gripper. During field tests, initial picking success rates for partially surrounded or isolated strawberries varied from 50% to 97.1%, depending on growth conditions. With a second attempt, success rates improved to 75-100%. Operating at swift speeds, the robot took merely 6.1 seconds in one-arm mode and 4.6 seconds in two-arm mode for manipulation tasks.

Arad *et al*. [32] developed and tested the SWEEPER, a robotic solution tailored for harvesting sweet peppers within greenhouse environments. This innovative system incorporates a six-degree-of-freedom industrial arm equipped with a custom-designed end effector, RGB-D camera, high-performance computer with a GPU, programmable logic controllers, and additional electronic components. Operational tasks are split between two Arduino-based PLCs, with one managing cart movements along rows and elevation, and the other handling low-level functions of the end effector. Development primarily utilized C++ and Python, leveraging ROS Indigo on Ubuntu 14.04. Over a 4-week testing phase involving 262 fruits, the average harvest cycle was 24 seconds, with logistics consuming half of this time. Notably, laboratory experiments suggest a potential cycle time reduction to 15 seconds by increasing manipulator speed. Harvest success rates varied significantly, with 61% under optimal conditions but dropping to 18% under current conditions, underscoring the critical importance of tailored crop conditions and varieties for effective robotic harvesting.

Yu *et al*. [33] designed an innovative robotic system tailored for harvesting ridge-planted strawberries. They proposed the R-YOLO model, specifically designed for accurately detecting strawberry poses during automated harvesting. This model demonstrated remarkable adaptability and real-time performance across diverse natural conditions and varying light intensities, effectively identifying multiple overlapping fruits. Test outcomes, based on 100 strawberry images, revealed an average recognition rate of 94.43% and a recall rate of 93.46%. Field trials further validated the system's efficacy, achieving an 84.35% harvesting success rate under modified conditions.

Kuznetsova *et al*. [34] designed a system for harvesting robots, integrating a customized YOLOv3 algorithm with tailored pre- and post-processing methods. These enhancements enabled efficient adaptation of YOLOv3 for apple detection in machine vision systems. Results showed an average apple detection time of 19 milliseconds, with 7.8% false identifications and 9.2% undetected apples.

Vrochidou *et al*. [35] proposed an integrated system architecture for Autonomous Robot for Grape harvesting (ARG), comprising three primary units: an aerial unit, a remote-control unit, and the ARG ground unit. The focus lies on the ARG, equipped to perform grape harvesting, green harvest, and defoliation. The ground unit incorporates an ORBBEC Astra 3D camera for navigation, mounted on the wheeled robot, providing an RGB-D map for obstacle detection. Processing tasks, including communication and machine vision algorithms, are managed by NVIDIA Jetson TX2 boards. These boards facilitate high-level autonomy and feature extraction for decision-making. Data transmission occurs via JSON packets.

Zhang *et al*. [36] unveiled a novel apple harvesting robot characterized by a unified system design and field-tested performance. Employing a sophisticated deep learning approach, the system integrates a Mask R-CNN backbone with an apple detection suppression end, yielding cutting-edge accuracy on their proprietary dataset. Complementary software algorithms facilitate seamless coordination among hardware components, enhancing the robot's efficacy in automating apple harvesting, especially in challenging orchard settings. Field trials conducted in two distinct orchards showcased the system's adaptability: in a young, well-pruned orchard, it achieved an impressive 82.4% harvesting success rate, whereas in an older orchard with dense, clustered branches and foliage, the success rate stood at 65.2%. Notably, the system demonstrated an average cycle time of approximately 6 seconds per fruit, encompassing both algorithmic processing and hardware execution.

Conclusion

The emergence of automated fruit harvesting robots offers a promising solution to the challenges of labor shortages and operational efficiency in agriculture. By integrating cutting-edge robotics, machine learning, and sensor technologies, these robots have the potential to significantly boost productivity and profitability on fruit farms while reducing dependence on manual labor. Their capacity to operate tirelessly and with precision across diverse environmental conditions ensures consistent fruit quality and yields. As technology progresses, further enhancements in design and functionality are anticipated, driving broader adoption and transforming fruit harvesting practices globally. In comparison to traditional and mechanical method, this proposed approach demonstrates enhanced versatility and resilience in non-structural environments, particularly in scenarios involving overlapping or concealed fruits and varying light conditions. This innovation holds the promise of revolutionizing fruit harvesting practices on a worldwide scale.

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