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Analysis of the Structural Design of Agricultural Machinery Arms in Practical Applications

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Abstract. The application of robotic arms in fruit and vegetable harvesting is receiving increasing attention. However, the current robotic arm design is mostly derived from the industrial paradigm, which is difficult to adapt to the dual challenges of the complexity of the agricultural environment and the diversity of crops, and there are problems such as excessive structural rigidity, insufficient environmental awareness, and a high harvesting damage rate. This paper focuses on the comparison of robotic arm structural design in typical fruit harvesting scenarios and a review of key technologies. This paper adopts the method of combining literature research and technology summarization, focusing on the core issues of the structural design of the robotic arm, such as the configuration of the degrees of freedom, the choice of drive and materials, the integration of the end-effector and the perception system, and systematically sorting out the current mainstream design solutions and typical engineering cases, comparing its adaptability and performance in the picking of apples, strawberries, dragon fruits, and other crops. At the same time, this paper analyzes the current technical bottlenecks of robotic arms in terms of environmental adaptability, cost-performance trade-off, agronomic suitability, etc., and proposes future development directions such as bionic structure design, group intelligence algorithms, and the integration of multiple-arm collaborative systems and smart orchards.

Keywords: Robotic arm, structure design, Agricultural Picking, Degree of Freedom Configuration, Sensing System Integration

1. Introduction

Against the backdrop of a tightening global labor supply and increasing demand for agricultural automation, research on the structural design and application of robotic arms in fruit harvesting has become particularly critical. Early explorations and prototype development of the programmable robotic arm concept applied to agricultural picking tasks occurred as early as the 1980s and were accompanied by advances in computer and machine vision technology. It was during that era that some of the world's first robotic arm picking prototypes were developed.

As time progressed, robotic arms have become the key to improving agricultural productivity, industrial manufacturing efficiency in modern factories, and solving labor shortages. In the field of fruit picking, the robotic arm must account for the complex challenges of fruit fragility and dynamic growth characteristics in an unstructured, non-uniform environment. Its structural design directly

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determines the picking efficiency, fruit integrity, and equipment adaptability. There are significant differences in the performance of different types of robotic arms when confronted with complex crop environments, such as picking apples in dense canopy areas and grapes among vines, which require very different robotic arm structural design needs. Fruit picking accounts for about 40% of the total workload of agricultural production, which means that nearly half of the cost of agricultural production comes from picking. However, traditional manual picking faces problems such as labor shortage, high cost, and low efficiency. For example, in China, due to a large number of rural populations moving into the city. The proportion of rural labor of the right age is decreasing year by year, while the area of facility agriculture has exceeded 4 million hm^2, so there is a need to alleviate the shortage of manpower using mechanization.

Due to the advancement and progress of mechanical and computer technology, numerous robotic arm-based agricultural picking equipment are now available on the market, which can significantly reduce labor costs. The strawberry picking robot “Lingzhan 1” developed by the team of Beijing Academy of Agricultural and Forestry Sciences is equipped with dynamic tracking and obstacle avoidance capabilities, and the picking operation space is three times that of the traditional industrial robotic arm, which can be used for picking strawberries, tomatoes, and other crops. Save more than 80% of labor [1]. The Korea Institute of Machinery and Materials (KIMM) has developed a collaborative system consisting of a harvesting robot and a transportation robot. The harvesting robot uses AI to recognize the location of the crop and a robotic arm to pick it. The system enables 24-hour operation and is 80% more efficient than manual labor. Robotic picking equipment has a bit more to offer than just lower labor costs, too. For example, improved working conditions and safety [2].

With manual picking, some picking tasks need to be carried out in hot, humid greenhouse environments or outdoors in inclement weather, which poses some health risks. Picking at height (e.g., some fruit trees) also poses a fall risk. If a robotic arm is used, the robot can work in environments that are uncomfortable or dangerous for humans, protecting the health and safety of the farmer. Robotic arm picking can also improve productivity and continuity of operation; manual picking speed and efficiency are limited by the number of workers, physical strength, and skill level, and cannot be a long-term continuous operation. Robotic arm picking machines can work for long periods, even around the clock, and picking speed and efficiency are stable. This ensures that crops are harvested in time during the optimal ripening period, avoiding yield loss or quality degradation caused by delayed picking due to human reasons, and improving overall production efficiency.

This study systematically compares structural design variations among 4- to 6-degree-of-freedom robotic arms in harvesting typical crops such as apples and citrus. By integrating perception technologies with agronomic compatibility requirements, it delineates performance limitations and application scenarios of different configurations. A novel "perception-driven structural optimization" paradigm is proposed, establishing a theoretical framework for developing cost-effective and highly reliable harvesting robotic arms. This approach facilitates the transition from laboratory prototypes to field-scale implementation while advancing the synergistic integration of agricultural mechanization with intelligent technologies.

2. Mechanical arm structure design technology

2.1. Degree of freedom configuration and kinematic modeling

The number of degrees of freedom (DOF) in a robotic arm directly determines its reachability and dexterity in three-dimensional space, consequently affecting its harvesting performance in complex

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orchard environments. In the field of agricultural fruit picking, the location of fruit distribution is variable, and the occlusion situation is complex, so a reasonable configuration of degrees of freedom is crucial to the performance of the robotic arm. The traditional three-degree-of-freedom robotic arm has a simple structure and is suitable for scenarios with regular fruit distribution, such as strawberry and tomato picking. However, such configurations exhibit limitations in spatial coverage and obstacle avoidance, rendering them inadequate for handling complex foliage occlusion scenarios. To solve the problem of complex vegetation scenes, the researchers used a five-degree-of-freedom robotic arm.

The incorporation of an additional redundant degree of freedom in five-DOF robotic arms—building upon four-DOF architectures—significantly enhances operational dexterity and obstacle avoidance capability, making them suitable for moderately complex orchard environments. Six-DOF robotic arms, on the other hand, are especially well-suited for orchards with dense foliage and uneven fruit distributions because they can manipulate space completely, allowing for arbitrary end-effector pose adjustment [3]. The Denavit-Hartenberg (D-H) convention has been widely used in kinematic modeling for both forward and inverse kinematic analysis of robotic manipulators. This approach uses systematic linkage parameter modeling to efficiently characterize the kinematics of robotic arms [4]. However, traditional approaches show significant shortcomings in unstructured agricultural settings when dealing with complex obstacles and dynamic variations. Researchers have integrated cutting-edge algorithms like deep reinforcement learning (DRL) to improve robotic manipulators' path planning capabilities in such complex scenarios. With Ciocarlie et al.'s new design, DRL significantly increases efficiency and indirectly boosts performance by roughly 15%. These cutting-edge methods greatly increase the intelligence level of robotic harvesting systems by enabling autonomous path planning and obstacle avoidance in unfamiliar environments [5].

2.2. Actuation systems and material selection

The selection of actuation mechanisms and structural materials has a significant impact on a robotic manipulator's payload capacity, dynamic response, energy efficiency, and environmental adaptability. For agricultural harvesting applications, robotic arms must meet the combined performance metrics of high precision, low power consumption, and lightweight design. As a result, choosing actuation methods and materials requires careful optimization.

Large fruits like watermelons and pomelos can be harvested with hydraulic actuation systems because they have a high payload capacity and are frequently used in industrial-scale robotic manipulators. However, these systems' low energy efficiency, high maintenance needs, and structural complexity limit their use in mobile agricultural robotics. Electric drive systems, characterized by rapid response, high control precision, and compact structure, have emerged as one of the predominant actuation solutions. They are particularly suitable for fruit grasping tasks requiring fast reaction and delicate manipulation [6]. Although the pneumatic drive is a little inferior in output stability and precision, its low cost and simple system structure make it suitable for scenarios that require less picking force, such as the graded picking of strawberries and tomatoes. In the tomato grading scenario, the pneumatic cutter can still work stably due to the low tomato stalk shear force requirement (about 5-10N), with a single picking time of 15 seconds, and a synergistic efficiency of the dual robotic arms of up to 120 pcs/hour, with a 40% reduction in the comprehensive cost. Carbon fiber has a density of only 1.7 g/cm³ (2.7 g/cm³ for aluminum and 7.8 g/cm³ for steel) and a tensile strength of up to 1500-2000 MPa (equivalent to 7-9 times that of steel and more than 2 times that of aluminum alloys).

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2.3. End-effector and perception system integration

In robotic picking systems, fruit integrity and harvesting efficiency are mainly determined by the cooperative performance of perception systems and end-effectors. Flexible grippers, bio-inspired cutting mechanisms, and vacuum suction devices are the primary types of end-effector designs that have been developed to meet a variety of fruit morphologies and harvesting needs. Flexible grippers are perfect for harvesting delicate fruits like peaches and strawberries because they use flexible materials to create finger-like structures. They are highly adaptable and have a gentle grasping action [7]. Cooperative performance of perception systems and end-effectors mostly determines fruit integrity and harvesting efficiency in robotic picking systems. The main forms of end-effector designs created to satisfy a range of fruit morphologies and harvesting requirements are flexible grippers, bio-inspired cutting mechanisms, and vacuum suction devices. Harvesting delicate fruits like strawberries and peaches is ideal for flexible grippers since their flexible materials build finger-like structures. They have a soft grasping action and great adaptation [5]. Concurrent with closed-loop control systems, force sensors integrated allow tactile feedback, so preventing too great fruit compression during grasping and so improving picking quality [8]. Modern agricultural robotic arms are moving toward integrated systems combining end-effectors with multi-modal perception (visual, tactile, etc.), to attain comprehensive automated control capabilities defined by "precise vision, accurate grasping, and stable harvesting." Furthermore, establishing the technical basis for the upcoming intelligent evolution of robotic harvesting systems is this combined design approach.

3. Application analysis of typical fruit picking scenarios

3.1. Tree crops such as apples and citrus

Robotic manipulators in arboricultural fruit harvesting—e.g., apples, citrus—must show exceptional canopy penetration capacity and obstacle-avoidance path planning to negotiate challenging foliage structures and irregular fruit distribution patterns. Integrated with apple tree 3D modeling, researchers have developed an enhanced ant colony optimization (ACO)-based 3D obstacle avoidance path planning method that greatly improves the path planning efficiency and obstacle navigation capabilities in complex orchard environments [9]. Researchers in citrus harvesting have created a flexible gripper picking technique based on target fruit recognition. This method combines a tailored end-effector design for citrus picking that greatly lowers fruit damage rates during harvesting with the YOLOv7 network model to attain high-precision citrus fruit identification [10]. With the new algorithm by Xu et al. the localization success rate is 87.15% and the picking success rate is 82.4%, which is higher than the accuracy of market robots.

3.2. Dwarf crops such as strawberries/tomatoes

Robotic arms for low-growing crops like tomatoes and strawberries have to be highly flexible and damage-free harvesting tool. Researchers have created a strawberry harvesting robotic arm driven by artificial intelligence with a cable-driven multi-joint architecture. This system uses fuzzy logic control to change manipulator posture, so obtaining effective and minimally invasive strawberry harvesting. It also combines deep learning models for fruit detection and optimal picking point identification. With a theoretical throughput of 720 fruits per hour, Chang et al.'s experiments revealed that single fruit picking time was 5–6.5 seconds, five times faster than conventional robots. In ideal lighting conditions, 82% of the pickings were successful. Additionally, a robotic system for

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harvesting strawberries grown in rows was created and assessed in a different study. The system detects and picks ripe strawberries in real time by combining visual perception modules with end-effectors. Its strong practical applicability is confirmed by field tests that show a high harvesting success rate under a variety of natural conditions [11].

3.3. Special form crops such as dragon fruit/pineapple

The asymmetrical growth patterns and intricate fruit structures of specialty crops with unusual morphologies, such as pineapple and dragon fruit, place additional demands on end-effector design. Through integration with the Robot Operating System (ROS), researchers have created a robotic system for apple harvesting based on the YOLOv5-RACF model that achieves high-precision fruit recognition and positioning. This algorithm by Zhu et al. achieves the advantages of accurate, real-time and efficient automated harvesting through Analysis of the structural design of agricultural machinery arms in practical applications - Fruit picking more than 98.7% of detected mAP, high-speed (0.13 s/trip) diameter measurement and 1-3 mm error control, combined with a lightweight design with 1.77 M parameters and 4.2 GFLOPS. This methodology provides useful reference insights for managing complex fruit architectures, despite being primarily developed for apples [12]. Researchers have created and assessed a passively compliant robotic picking system for citrus harvesting operations that exhibits exceptional flexibility and steady grasping performance, enabling it to handle citrus fruits of varying sizes and shapes [13].

4. Current technological challenges and solution paths

4.1. Environmental adaptation bottlenecks

Foliage occlusion significantly reduces the accuracy of target fruit detection and localization in unstructured environments, such as orchards, by impairing vision and depth sensor performance. Researchers proposed a fruit detection framework based on temporal deep learning and multi-view fusion to get around real-time perception bottlenecks. The system uses distributed camera arrays combined with Convolutional Long Short-Term Memory (ConvLSTM) networks to predict and reconstruct occluded areas during motion, achieving over 90% detection recall. Industrial robotics has effectively employed online replanning technology to satisfy dynamic trajectory correction requirements. In unexpected obstacle scenarios, Lee reduced collision rates to less than 1% by combining the Fast-Marching Method with real-time point cloud updates [14]. By incorporating graph optimization modules into local controllers, similar techniques can be applied to agricultural harvesting manipulators, allowing for millisecond-level trajectory adjustments.

4.2. The cost-performance balancing dilemma

Large-scale adoption is hampered by the high cost of highly precise, multipurpose customized robotic arms. Prototype development costs can be decreased by combining open-source electronic control platforms (like ROS-Industrial) with lightweight, 3D-printed components. One commercial robotic platform achieves repeat positioning accuracy of ±5 mm while keeping system costs under $5,000 for agricultural applications by combining PLA-printed grippers with aluminum alloy modular arm segments.

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4.3. Insufficient agronomic suitability

Crop growth characteristics are frequently overlooked in robotic arm designs, which leads to less than ideal operational efficiency. Researchers recommend using crop growth models early in the workspace planning process to improve agronomic compatibility. In high-density greenhouse environments, multi-arm collaborative systems can cut single-arm operation time by an average of 25% by utilizing digital twin platforms for collision detection and real-time scheduling [15]. In order to accomplish effective, low-damage harvesting throughout the whole growth cycle, future advancements may combine adaptive workspace algorithms with crop growth stage prediction.

5. Future research directions

5.1. Combining population intelligence algorithms with the design of bionic structures

Robotic arms with bioinspired structures have a great deal of promise for effective grasping and compliant adaptation. For example, flexible grippers modeled after octopus tentacles use tendon-driven mechanisms and materials with varying stiffness to achieve adaptive envelopment of fruits with irregular shapes. Future work could use swarm intelligence algorithms. Examples are ant colony optimization. Examples are bee algorithms. These methods help multi-arm systems make decisions together. They also help plan cooperative paths. This approach avoids central controllers. Multiple robotic arms share environmental data directly. They plan tasks together. Tasks include avoiding obstacles. Tasks include harvesting [16].

5.2. Low-power drive technology and lightweight materials

Lightweight materials and low-power drive systems are important. They help robots move better. They also make batteries last longer. Using carbon fiber composites helps. Using efficient titanium alloy hinges also helps. These materials reduce arm weight significantly. Weight decreases by over 30%. The structure stays strong. By recovering kinetic energy during end-effector return motions and achieving sub-watt static power consumption for actuation, senseless permanent magnet synchronous motors (PMSM) with intelligent energy recovery control greatly increase overall energy efficiency.

5.3. Cooperative multi-mechanical arm operation and integration with smart orchard systems

In the future, orchards will develop into IoT ecosystems and robotic collaboration platforms. Multi-arm cooperative systems can use distributed vision-force fusion. This method combines environmental data and crop growth data. It puts this combined data into digital twin systems. Then, real-time task scheduling becomes possible. Collision avoidance is also optimized. These systems connect to intelligent orchard management platforms. This integration lets them change robotic operation schedules dynamically. They can also change robotic paths dynamically. This improves fruit quality. It also improves harvesting efficiency.

6. Conclusion

As the global agricultural labor shortage intensifies, robotic-arm-based intelligent picking systems are emerging as a key solution to the “last mile” challenge in fruit and vegetable harvesting. This

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paper reviews current progress in robotic arm structural design, focusing on key elements: degree-of-freedom (DOF) configuration, actuation methods, end-effectors, and perception systems.

This study examines common crops. Examples are apples, strawberries, and dragon fruit. It tests design adaptability in different environments. The work highlights key challenges. These include poor farm integration. They also include high costs. Visibility issues also exist. Researchers also explore promising research directions. Examples are swarm intelligence. Examples are bioinspired structures. Examples are low-power actuators. Examples are smart orchard systems. Robotic arm design now uses a "perception–optimization–adaptation" loop. In practical terms, robotic arms are becoming increasingly scalable and affordable due to modular and standardized designs. Their wider deployment is now feasible, especially in small to medium-sized farms, thanks to open-source software, 3D printing, and universal control platforms.

In conclusion, the structural design of robotic arms is essential for the development of smart agriculture. Its intelligence, adaptability, and system integration capabilities will support a more sustainable and advanced farming future, influencing the pace and scope of agricultural robotics.

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