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DEVELOPMENT OF AN AUTONOMOUS STRAWBERRY HARVESTING ROBOT

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Abstract**—** The increasing demand for automation in agriculture drives the need for the development of autonomous crop harvesting systems. This paper presents an autonomous strawberry harvesting system that utilizes computer vision and adaptive trajectory planning to achieve this. A 6-degree-of-freedom (6-DOF) robotic manipulator was used in conjunction with a stereo camera to detect, localize and pick strawberries. The system was validated through experimental tests in both laboratory settings and real farm environments. Initial results indicate progress in automating the harvesting process although variations in strawberry stem orientation pose challenges for repeatability.

Keywords- Autonomous Harvesting, Strawberry, Robotic Manipulator, Path Planning)

I. INTRODUCTION

The need for automated harvesting in sustainable agriculture is growing rapidly as labor shortages, rising costs, and increasing food demand put pressure on traditional farming methods. Recent developments in agriculture are focusing on integrating robotics systems to increase productivity and efficiency. However, to achieve high results it is necessary to develop robust navigation and computer vision systems that allows robots to work safely in farms environments [1]. For cases where crop manipulation is needed, particularly for delicate produce such as strawberries, some technical challenges can appear. These challenges include the need of robust perception pipelines to accurately identify strawberries in different light conditions, a precise stem location algorithm and usually a custom end-effector that can pick ripe strawberries out of clusters without damaging others in the process [2]. In other words, a mechatronic solution that can minimize these challenges will become a good option to disrupt an increasing global market for agricultural robots expected to reach USD 17.29 billion by 2030, although this will also introduce some ethical considerations that major stakeholders such as farmers, authorities and manufacturers should evaluate [3].

This paper presents a sequential harvesting architecture that leverages computer vision techniques, adaptive trajectory planning, and real-time correction of trajectories errors, thereby enhancing efficiency and minimizing failure rates. A 6 Degree of Freedom (DOF) robotic arm acts as the core of the solution presented in this paper. The current system configuration, with the robotic arm mounted on a mobile platform with storage capacity, is shown in Fig 1. Optimizing its planning and execution timing could potentially reduce the gap between machinery and human picking time. Additionally, a camera mounted on the wrist of the robotic arm was carefully calibrated to identify strawberries using a fine-tuned You Only Look Once (YOLO) model, which determines whether the berry is ready to be picked. Moreover, a custom end-effector was developed to efficiently maneuver between groups of strawberries. By developing an optimized robotic harvesting system, this study aims to contribute to the advancement of autonomous agricultural solutions that support year-round labor-efficient strawberry production.

Recent research has shown that computer vision (CV) integration into robotic applications requires careful review data available and labeling strategies to use. Moreover, common CV used falls into three main categories of detection: 2D bounding box (BB), instance mask segmentation (IMS), 3D oriented bounding box (OBB). However, the fundamental challenge faced on this domain is acquiring enough real-world data to train robust CV models. A survey completed during 2020, highlighted that since 2015 precision agriculture experienced an increase in public dataset available for specific tasks, with weed control and fruit harvesting having the largest dataset types available, totaling 15 and 10 datasets respectively [4]. Barth et al. discussed how to mitigate the effects of data scarcity on a vision model with the use of 3D models to generate synthetic images [5]. Their method employs GANs to enhance the realism of these generated images. Other researchers also adopted data augmentation techniques, which included PCG-based synthesis and image shading to scale up dataset size while maintaining realism [4].

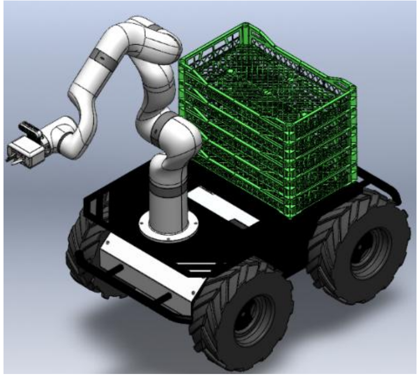

Figure 1. Robot current configuration design.

Additionally, recent research has found critical challenges in agricultural CV systems related to environmental variability and computational demands. As highlighted by Ghazal et al. varying lighting conditions, weather conditions and vegetation occlusions notably affect system performance. To address these issues, researchers proposed integrating images technologies such as RGB, multispectral, hyperspectral or thermal that can provide complementary data to improve the robustness of CV systems [6].

Autonomous agricultural robots offer a significant potential to decrease labor costs and to improve productivity. However, to achieve this, navigation capabilities play an important role in successfully deploying robots in the fields and diverse perception modules must work together to enable the robot to execute precise crop movements and environmental adaptation. Recent advancements have shown that LiDAR-based systems through optimized algorithms, achieved enhanced accuracy in crop row identification [7], while other variants such as 3D LiDAR usage have showcased better performance in scenarios where GNSS use is limited [8]. The integration of deep learning-based vision systems has improved real-time obstacle detection and environmental interpretation capabilities [9]. Analysis demonstrated that laser-based simultaneous localization and mapping (SLAM) systems achieve higher precision in accuracy in critical applications [10]. Moreover, multi-sensor fusion techniques incorporating LiDAR and vision sensors, and other sensors such as global position system (GPS) and inertia moment unit (IMU) can enhance navigation reliability in complex environments [9].

Recent advances in robotic arm path planning algorithms have shown improved efficiency and adaptability in complex environments. Li et al. suggested the Adaptive Step Rapidly exploring Random Trees* (AS-RTT*) algorithm for tea-picking robotic arms. This algorithm achieved significant improvements, demonstrating a 14.8% reduction in path length compared to traditional RTT* and completing planning tasks in under one second. The AS-RTT algorithm demonstrated showed efficient navigation through dense obstacle settings typical of tea farming environments [11]. Building on this foundation, Cao et al. created an enhanced RTT*-Connect algorithm by incorporating target bias sampling and dynamic step size adjustment. This enhanced version achieved a 19.39% reduction in average runtime compared to traditional RTT*-Connect algorithm while maintaining a 100% success rate in complex environments [12]. Huang et al. developed a novel RTT*-Connect algorithm combining elliptical space sampling techniques with repulsive potential fields. It improved obstacle avoidance capabilities and computational efficiency. Additionally, by testing in both simulated and real environments, the algorithm demonstrated a 5% reduction in path length and improvement in handling dynamic obstacles [13].

All these areas of research are thoroughly developed, however, the integration of each component into an all-encompassing solution to autonomous harvesting is not currently available. This study aims to address this research gap by integrating autonomous navigation, computer vision and robotic manipulator path planning to create a fully autonomous strawberry harvesting robot. The structure of this paper following this section is detailed as follows: Section II explains each subsystem of the autonomous harvesting robot and explains what methods are used to deploy them and how they interact with each other, section III describes the environments in which the tests were conducted, section IV details the results of the tests done in the farming environment, section V concludes the paper and summarizes the results as well as detailing the future direction of the project

II. System Design & Methodology

This section presents the methodology for deploying the autonomous harvesting robot. The implementation encompasses three main components: CV for detection and localization, robot arm path planning for optimal trajectory generation, and autonomous navigation for efficient movement through the field.

A. *Robotic Arm Hardware and Control*

The UF850 Robotic Arm [14] was selected as a 6-axis robotic manipulator for this application due to its range, speed, repeatability, and payload. All these specifications meet the requirements for the scope of work being performed. They are summarized in Table 1 and visual representation can be seen in Fig. 2. The arm is also compatible with Robots Operating System (ROS) packages utilized during the development of the strawberry picking process flow. The trajectory planner used to perform the inverse kinematics from the given strawberry to the robot base is the OMPL with the geometric planner RRT*.

TABLE I. UFACTORY UF850 ROBOT SPECIFICATIONS

Specifications	Values
Range	850 mm
Speed	500 mm/s
Repeatability	$\pm 0.02\,mm$
Payload	5 kg

Figure 2. Robotic arm hardware

B. Computer Vision System

For the application of autonomous farming, computer vision plays many important roles. This robot utilizes computer vision in two main ways. The first use of computer vision in the harvesting system being is strawberry detection and localization. A YOLO machine vision model takes in an image from a stereo camera and can identify all strawberries in the image and return a set of 3D coordinates for each strawberry in the frame. This list of coordinates can be used by the planner to determine the joint movements required to move to the strawberry location for harvesting. The second application of computer vision in this system is for determining the health of the strawberry. The first module detects strawberries from a further scanning position to capture more strawberries in the frame. Compared to the first scanning position, the second scan is performed much closer to the strawberry to capture a higher resolution image, which is required to determine if the strawberry is healthy, ripe or damaged. These attributes determine whether a strawberry is ready for harvesting, not yet ripe, or damaged and needs to be picked and discarded. The combination of these two applications allows the robot to detect and locate strawberries as well as determine if they should be harvested.

C. Path Planning Algorithm

For an autonomous harvesting robot, having a robust picking system is integral to the performance and reliability of the system. There are multiple factors to consider when defining the process flow for harvesting in terms of what planning and execution operations must occur and in what order. To maximize the efficiency of the picking process, it is essential to optimize the actions performed by the robotic manipulator to ensure no time or energy is wasted. Before optimizing the order of picking, its process flow for each strawberry must be defined. This operation consists of several stages: approach, cutting, and drop-off. The approach stage ranges from the current position (usually the last drop-off position) to the strawberry health check position, relative to the strawberry currently being processed, where the secondary scan is performed to see if the berry should be harvested. Once the strawberry is deemed ready to pick such that it is ripe and healthy, the arm will perform a cartesian movement to the picking site where the harvesting will be performed. The robot will then begin the drop-off phase by performing a similar cartesian movement in reverse to get to a safe plane before moving to the drop-off location. The purpose of this drops-off motion being composed of two stages is to prevent any potential collisions between the arm and the troughs in which the strawberries are going. To further optimize this system, a planning pipeline was used to perform parallel path planning for subsequent strawberries to be picked. The order in which the strawberries are picked is also imperative, as this can be another source of wasted time and motion. The strawberry order is determined by implementing an algorithm that solves the traveling salesman problem (TSP) and generates the shortest round-trip path between all strawberries. The shortest path of a set of five strawberries can be seen in Fig. 4. This becomes important when replanning is necessary due to invalidated specific strawberry path plans. This invalidation may occur for a few reasons, if the robot is not able to reach the destination due to an invalid movement such as a singularity, or if the strawberry is deemed not valid for harvesting at the secondary scan. Once a plan is invalidated, it becomes necessary to replan some movements from the next strawberry in the list, since the assumed starting position has changed. If the list of strawberries is ordered to minimize the total distance between all strawberries, this will also translate to time savings when moving to the next strawberry. For example, if the health check deems the strawberry not valid for picking, the subsequent drop-off process must be invalidated. As a result, the robot position will be very close to the next strawberry in the list, minimizing the next approach motion. A flow chart describing the strawberry detection and harvesting process flow can be found in Fig. 3.

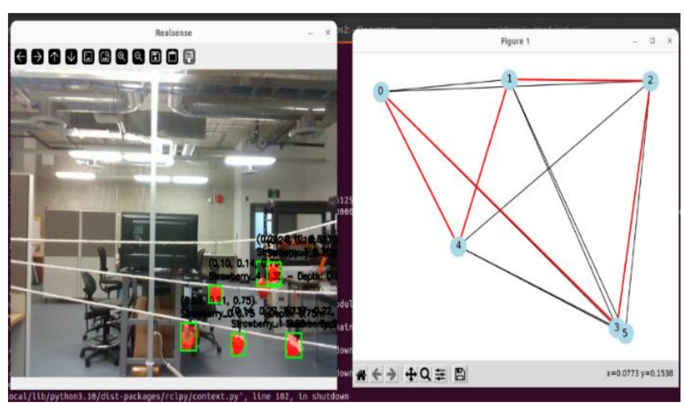

Figure 4. Strawberry queue with artificial strawberries.

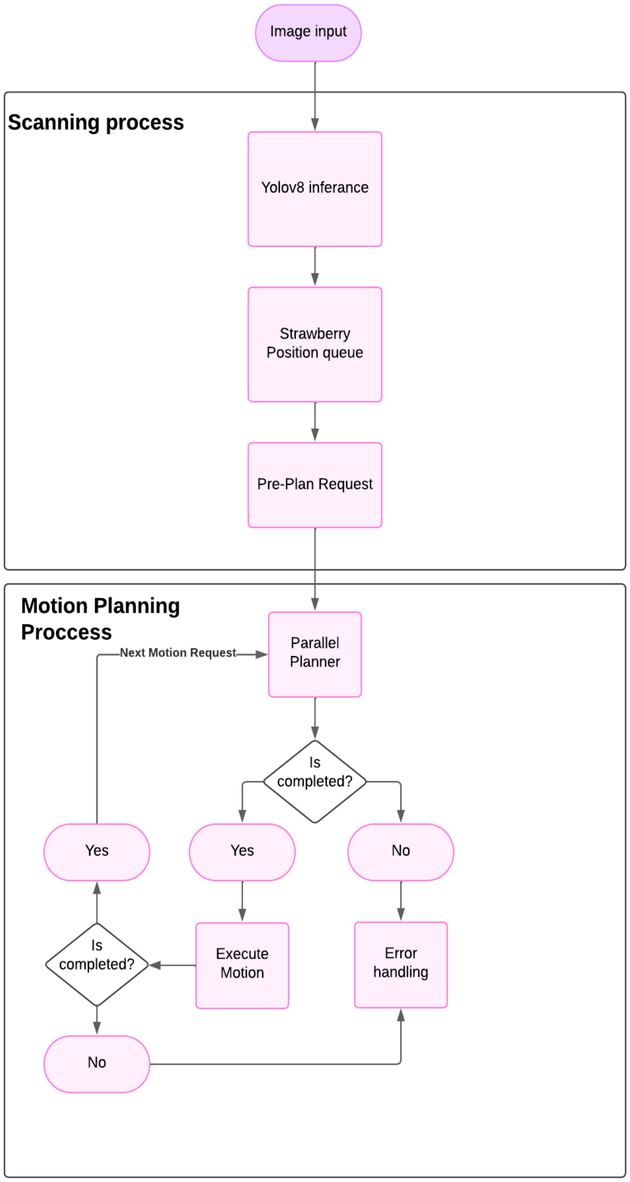

Figure 3. Path planning workflow algorithm.

D. *Navigation System*

Autonomous navigation is a main component of the automated harvesting process. This enables the robot to harvest areas much larger than the work envelope of the manipulator. Through integrating autonomous navigation and path planning with the harvesting subsystem, a full autonomous system can be deployed. For this system, the hardware used is the Clearpath Husky mobile base, Velodyne VLP-16 LiDAR [15], SwiftNav Duro GPS [16], and MicroStrain 3DM-GX3-25 IMU [17]. The integration of these components results in a system that can perform simultaneous localization and mapping (SLAM). With this, a map of the farm area can be generated, which the mobile base will traverse. The GPS is used for global navigation and the LiDAR is used for localization as well as local navigation. This local navigation can detect and avoid obstacles when traversing along a generated path corresponding to a goal point. With this system, the robot can traverse the aisle of the poly tunnel, harvesting frames of strawberries at a time. The robot remains stationary while harvesting and once the queue of strawberries has been processed, the robot indexes forward. The robot will move a short distance forward such that a new image will be captured and there will be some overlap with the previous image frame. The purpose of this is to ensure no strawberries are missed.

III. Experimental Setup

The robot should be adaptable to various environments so long as the vision system is robust enough with a diverse dataset. For development, this robot was predominantly used in a laboratory with artificial strawberries that were hung at various positions along a set of clotheslines. A minimum of five strawberries were used during testing to test the capability of the vision system as well as the effects of strawberry clusters on the picking mechanism. As for testing, this robot was brought to a farm and tested on various strains of strawberries that were growing in troughs at a height of approximately 1.15 m as seen in Fig. 6. Tests were performed with natural light during the day on the farm, minimal light during the evening on the farm, and with artificial light in the laboratory. Additionally, an offset of approximately 0.03 m between the strawberry location and robot end position was consistently observed, as seen in Fig. 5. This is a small enough offset that the strawberry can still be picked but is large enough that another strawberry from the same cluster may be mistakenly harvested as well. These findings and the experimental setup can be seen in Figs. 5 and 6, respectively. While testing, the manipulator was mounted to the mobile base to ensure the same conditions for both laboratory and farm testing environments. The battery and manipulator controller were both mounted on the base. These components as well as the base were set up as boundary zones for the planner. As a result, the planner will avoid these specified zones, thus preventing any possible collision. The manipulator was also not operated at full speed both in the laboratory and on the farm as to avoid any collisions that may occur due to unexpected paths generated, or in the case of the farm testing, any potential collisions with the strawberry troughs. The controller was also equipped with an E-stop as an additional safety measure.

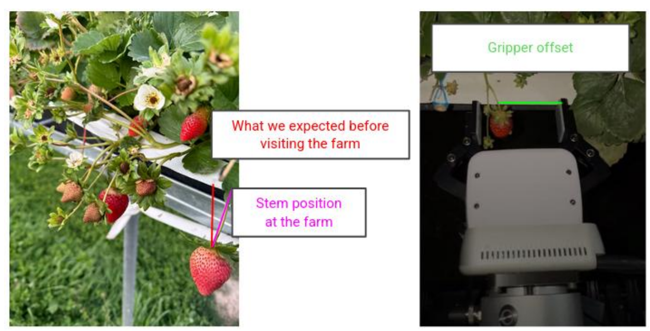

Figure 5. Field observations: discrepancies in expected and actual strawberry positions.

Figure 6. Polytunnels at partner's farm.

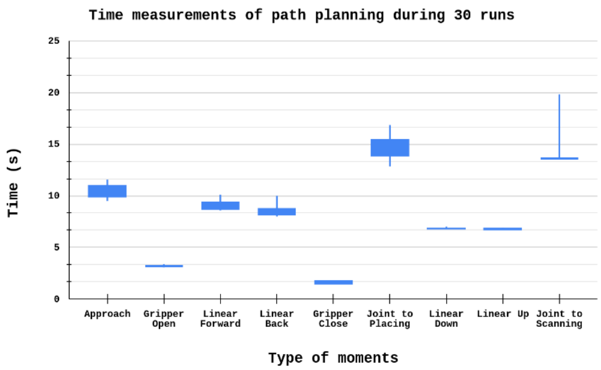

Figure 7. Box Plot of path planning and execution time

IV. RESULTS AND DISCUSSION

The tests at the farm and the lab with the robot arm prove successful but demonstrate many areas for improvement that would make the system more robust. The arm was able to repeatedly approach strawberries for harvesting and successfully and sequentially process strawberries. However, despite the end position being repeatable, there was a consistent offset that was observed from the end effector relative to the strawberry stem. It was observed that many of the strawberries in the troughs from the farm test had more variation in the orientation of the strawberry and stem position than that of the experimental laboratory setup. This reveals the need for further development of stem localization through additional image processing. The robot arm was mounted to the mobile base but was teleoperated for these tests as the integration between the autonomous navigation of the mobile base and the harvesting process of the robot arm has not yet been completed. Through repeated trials, the processing time was obtained for the previously mentioned process flow of scan, sort coordinates, approach, pick, drop off, and repeat. After 30 cycles, the average for each stage was determined as shown in Fig. 7. For this trial, parallel path planning was not utilized to show the time savings available by implementing this process. The large variation seen in the box plot of the figure exhibits the additional cycle time impact of planning sequentially compared to in parallel or concurrently. Additionally, as mentioned in the previous section, the manipulator was running at 50% speed. With the parallel path planning implemented and the speed increased to its full capability of 500 mm/s, significant improvements on cycle time will be observed.

When comparing the results of the laboratory testing to the farm, the repeatability of the system was similar, but the lab setup did not entirely replicate the environment observed at the farm. For strawberries that had similar orientation to the lab tests, the stems plane is near perpendicular to the gripper plane, provided no difficulties in being harvested. However, a large majority of the strawberries in the trough did not conform to this. Some strawberries were almost parallel to the gripper such that the vision system could identify the strawberry, but the stem was fully occluded by the strawberry. With the current sequence for picking, these strawberries were not able to be successfully harvested highlighting the need for improving the manipulator approach angle and stem position detection. As for why the strawberries were positioned in this way, the trough was equipped with a skirt that would elevate the strawberries to allow the farm labourers to harvest the berries easier. This skirt could be removed if the farm was intended to be fully autonomous, although it is still important to develop the robot further to be capable of harvesting in these more complex scenarios.

V. CONCLUSION AND FUTURE WORK

In this paper, the process of developing an autonomous strawberry harvesting robot was presented. This was done by integrating a 6-axis robotic manipulator, computer vision, and path planning and execution algorithm. This robot was tested in both laboratory and farm environments. Through these tests it was found the system is capable of autonomously detecting, localizing and picking strawberries. The mobile base is capable of mapping and traversing a known environment autonomously but is not yet integrated into the harvesting submodule.

After observing the outcome of real environmental tests, it was found that further developments to the computer vision component is required to better orient the end effector approach. The application of 6DoF pose estimation would be applicable here. Additionally, in terms of robotic arm path planning, there is an opportunity to improve the results of the planner with the usage of reinforcement learning (RL). There is a possible shorter path that can be found by minimizing the Hamiltonian path between all the strawberries in the queue.

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