Title:
Exploring A Novel Automated Cucumber Harvesting Framework

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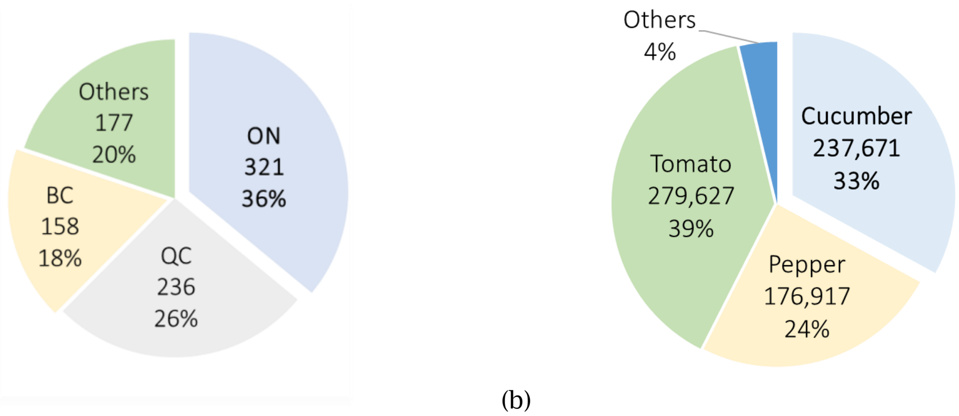
Keywords:
3D Camera, Image Detection, YOLO, Shape and Color Features, Cucumber Characteristics

DOI: 10.14733/cadconfP.2025.189-193

Introduction:

Windsor-Essex in Ontario, Canada, has one of the highest densities of greenhouses globally (second to the Netherlands), and most of Canada's greenhouses are located in Ontario. Statistics prepared by the Canadian Greenhouse Vegetable industry illustrate the greenhouse distribution and the volume of production associated with greenhouse produce [2, 5], and it can be seen that cucumbers production volumes are very high (Fig. 1). Despite housing only 36% of the total number of greenhouses, Ontario greenhouses produce 71% of the greenhouse products, underscoring the presence of larger greenhouses, more fertile soil and ready availability of water resources in the province. In fact, the distribution of costs indicates that gross yearly payroll is the major expense (29%), operating expenses are 22%, other crop expenses, such as fertilizer and pesticides, are 19%, and plant material purchases are 15%. Manual cucumber harvesting is common in greenhouse environments, but this is labor-intensive, and the quality, speed, and efficiency of the harvesting heavily rely on the workers' skills and physical strength. In 2021, approximately 5,000 workers were employed in Canadian cucumber greenhouses, encompassing both permanent and seasonal labor. Particularly during the COVID-19 pandemic, labor shortages posed challenges for greenhouse operations.



(a) (b)

Fig. 1: (a) Statistics on the distribution of commercial greenhouses in Canada out of a total of 892 greenhouses, (b) Statistics on the distribution of greenhouse production volumes (in metric tons) in Canada.

Automated methods of harvesting are being considered as a viable alternative, but this is not a mature solution. Research in automated agricultural robots often focuses on one or two specific system components: produce detection, innovative grippers, robotic arm efficiency, autonomous functions, and mechanical harvesting alternatives. However, comprehensive research on semi or fully automated harvesters is limited. There are many studies focusing on detection aspects solely [4, 5, 8]. Image detection is challenging due to the location, orientation, and variable shape characteristics of the produce, as well as the shadows cast due to the leaf and light source locations. Image processing for detection requires specialized platforms, and ImageJ and Fiji, open-source programs, were explored for suitability. In this study, segmentation and thresholding are performed initially, followed by utilization of some detection plugin to identify the borders and edges of plant components. The results of applying colour threshold and some other filters, are shown in Fig. 2. Unresolved is the ability to accurately extract the boundaries of cucumbers while excluding the vines and leaves' boundaries.

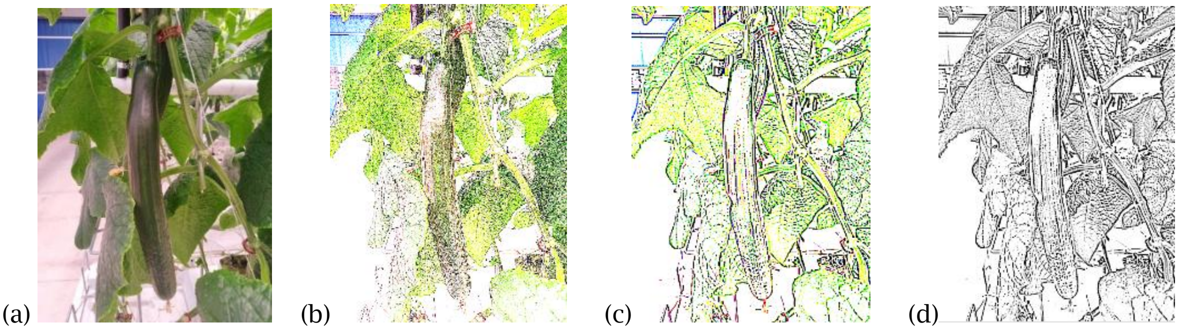


Fig. 2: (a-d) Image J results for filtering and extracting the boundaries.

In this study, a new method of detection is put forward, and a semi-automatic solution is tested for this robotic harvesting framework. It is hypothesized that manipulating *XYZ* point cloud data simultaneously with the RGB data will provide a basis for effective real-time image processing and harvesting based on this preliminary work.

<u>Main Idea:</u>
The implementation roadmap is presented (Fig. 3) along with an overview of the proposed cucumber harvester system (Fig. 4 (a)), which includes four primary components: 1. an image processing unit, 2. a robotic arm, 3. a cutter, and 4. a container to hold the cut cucumbers. The focus of this paper is on a new detection method, although the research included all elements. For the first step, the cucumber is detected. Then the position of the cucumber stem end is used as input to generate a robot trajectory (a Universal Robots collaborative robot UR3e [6]). For the third stage, the robotic arm cuts the cucumber from the stem end.

In this study, cutting blades were placed in 3D printed brackets, which were embedded at the TCP of the UR3e robot. A developed Python script receives the data captured by the 3D camera. For the hardware configuration for this roadmap, a compact and lightweight collaborative robotic (cobot) arm is used as the base test system [6]. An artificial greenhouse featuring 3D printed peppers, cucumbers, and apples, with some artificial leaves and vines is utilized for the testing. This system has produce of different colours (Fig. 4 (b)). The leaves, vines, and cucumbers are very similar in coloration, increasing the detection challenges. As well, and the artificial cucumbers can be hidden behind vines and leaves. The camera, mounted on the robot's head, can adjust its angle and position to capture images from multiple viewpoints. This capability enables the detection of cucumbers that are obscured from certain angles.

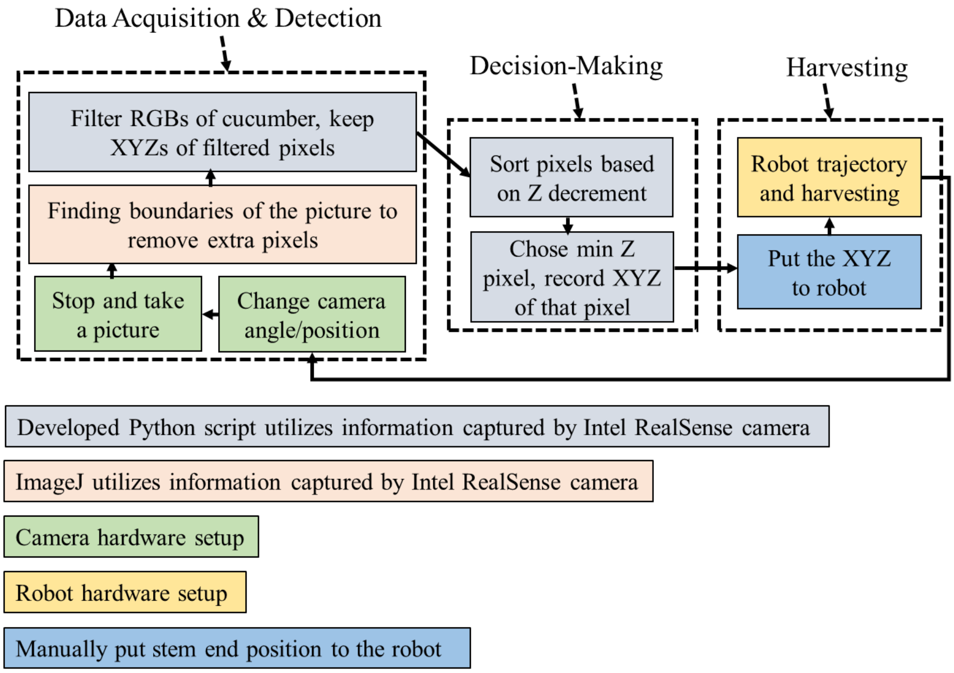


Fig. 3. Implementation roadmap of different steps

A 3D camera is employed to collect the colour and shape data, an Intel RealSense D435if camera. Intel's RealSense D435if camera employs LiDAR and stereo depth technologies [3]. Operating on USB 5V power, the D435if captures colour and XYZ data simultaneously, producing a point cloud for scene reconstruction. Different software tools were employed to detect and characterize the cucumbers. Several machine learning strategies were explored, and problems related to data sufficiency were identified. RoboFlow, used for computer vision applications, was used for dataset manipulation. RoboFlow is an automated platform designed to streamline object detection, image classification, and segmentation. Python was used to implement or interact with you only look once (YOLO) YOLO-based object detection algorithms and manipulate the 3D camera dataset. YOLOv8 was utilized for this research. In this study, both pose estimation and object detection models were employed. The computer vision annotation tool (CVAT) was utilized for labeling images intended for image processing purposes. Prior to training, it was necessary to label cucumbers.

F1 scores and confidence are metrics used in this study. The examination of the cucumber bounding box and key point detections is conducted, and selected results are showcased. Fig. 4 displays two images in which cucumbers are detected in the YOLO model, accompanied by their respective detection confidence for each cucumber. There is no false positive being detected. However, few false negatives were observed, primarily because very small portions of cucumbers are visible in some cases. The percentage of correctness for each detected cucumber bounding box is shown in the figure. The metrics are presented in Tab. 1. The results demonstrate that cucumber detection accuracy improves significantly with the keypoints YOLOL method, achieving a confidence score of 0.502 and an F1 score of 0.82.

When employing the raw RGB-XYZ data from the 3D camera, first a color analysis on the target cucumbers and plant components is done, where the vines, leaves, stems, and other plant components were evaluated to establish filters. Rules to identify plant components are developed based on the color analyses.

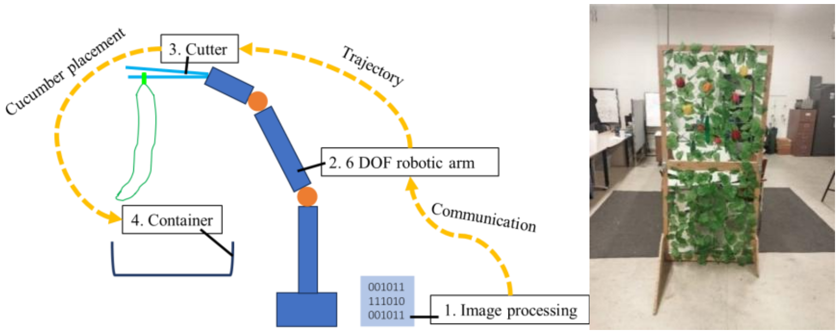


Fig. 4: (a) An automated cucumber harvester includes four main components: detection system, robotic arm, cutting edge, and cucumber placement, and (b) the greenhouse testing mockup.

Fig. 5: Two images with their detected cucumbers and confidence levels [1].

Model	F1	Confidence
YOLOL	0.55	0.204
YOLON	0.38	0.121

a

Model	F1	Confidence
YOLOL	0.82	0.502
YOLOX	0.42	0.053

b

Tab. 1. Summary of metrics for cucumber detection (a) bounding box and (b,) keypoints detection.

Once the elements are identified by color and positional data, the *XYZ* point cloud data is leveraged. Using the calibrated *XY* data, the sizes of cucumbers and the position of the stem end can be identified. With the *Z* data, the distance between the robot and the cucumber was determined (an offset is required to contact the stem, and this is ongoing work).

Fig. 6: Robot 'harvesting' detected cucumber [1].

Preliminary results are promising. Ongoing internal tests and tests in greenhouse environments need to be conducted during the growth and harvesting cycles in different lighting conditions. Automation can be applied in non-standard working hours and the lighting / shadow conditions vary at night and shadows vary over the year. Another challenge is to develop trajectories that do not touch the leaves (or limit contact). There is significant research yet to be conducted, but fusing point cloud data analyses with contemporary image analyses provides new opportunities to meet these challenges.

Conclusions:

Cucumber harvesting automation strategies are being explored as there are issues with labor availability and the potential of injuries associated with the repetitive tasks being performed in non-ideal postures. A key element of an automation solution is the detection of the cucumbers in 3D space, and this is not a mature area of research. When utilizing flat images, and tools such as ImageJ, the boundaries are extracted for plant components, but alternative analyses need to be performed to identify the components and isolate cucumbers. Employing a 3D camera and analyzing RGB and *XYZ* point cloud data provides new opportunities. Introducing reverse engineering approaches with image detection has the potential to introduce solutions that are scalable and extendable. The stem position and shape data can be extracted from the point cloud, enabling a robotic arm to 'snip' a cucumber in the artificial test setting. It is proposed to continue to utilize 3D cameras along with reinforcement learning algorithms to improve plant component detection, not only for developing robot trajectories for harvesting, but for collision avoidance (avoiding leaves, and other features/infrastructure).

Acknowledgements:

The support from the Office of Research and Innovative Services at the University of Windsor and JEM Farms is gratefully acknowledged.

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