AI-enabled 3D vision system for rapid and accurate tree trunk detection and diameter estimation

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A paper from the Proceedings of the
16th International Conference on Precision Agriculture
21-24 July 2024
Manhattan, Kansas, United States

Abstract.

Huanglongbing (HLB) is the major threat to citrus production in Florida and oxytetracycline (OTC) injection was proven to be effective in controlling HLB. The total amount of OTC that needs to be injected for HLB-affected trees depends on the trunk diameter. Therefore, precisely measuring trunk diameter is important to effectively control HLB. However, manually injecting OTC and measuring the trunk diameter is time-consuming and labor-intensive. A previous study has developed a needle-based trunk injection system to rapidly inject OTC in HLB-affected trees. This novel technology requires a vision system to detect the tree trunk, estimate the trunk diameter, and locate the injection point(s). Therefore, this study developed an automated 3D vision system mounted on the needle-based trunk injection system to accurately detect the trunk and measure the trunk diameter and distance between the camera and injection site by using a deep learning method (YOLOv8) and an RGB-D camera (Realsense D435i). A total of 324 images were collected and labeled to train the YOLOv8 model for tree trunk detection and segmentation. Then, the YOLOv8 model and the Realsense D435i camera were tested for citrus trunk segmentation and trunk diameter estimation in a citrus orchard. The result shows that the mean average precision of trunk segmentation was 0.99 and the correlation coefficient between trunk diameter estimated by the RGB-D camera and ground truth was 0.91. The development of the 3D vision system can speed up the trunk injection progress, which can save money and reduce the application time. Currently, the deep learning model was deployed on a desktop computer with an NVIDIA GTX 1080 Ti graphics processing unit (GPU). In the near future, the deep learning model will be deployed and tested on the edge device (NVIDIA Jetson nano). Then, a low-cost 3D vision system can be integrated with the needle-based trunk injection system for real-time tree trunk injection.

Keywords.

Citrus greening, computer vision, deep learning, HLB, object segmentation.

1. Introduction

Florida citrus production was severely affected by Huanglongbing (HLB) or citrus greening (Home et al., 2007). Many control methods have been explored to reduce citrus yield loss due to the HLB, including thermotherapy (Ghatrehsamani et al., 2021, 2019b, 2019a). However, there is still no cure for HLB, which has led to the reduction of citrus production in Florida these years. A recent study shows that oxytetracycline (OTC) injection was an effective method to manage HLB-affected trees (Archer and Albrecht, 2023), and the trunk diameter affects the total amount of OTC that needs to be injected into a tree.

However, manually injecting OTC and measuring trunk diameter is very slow and growers need to hire lots of people for this task. Therefore, Ojo et al. (2024a, 2024b) developed a needle-based injection system for HLB control. However, the current system is not able to automatically locate the tree trunk and measure the trunk diameter to guide the injection system to move to the injection positions and inject the right amount of OTC for effective HLB control. Therefore, a vision system that can provide this information for the injection system was needed.

Deep learning has been widely applied in agriculture (Bereciartua-Pérez et al., 2022; Kamilaris and Prenafeta-Boldú, 2018; Yun et al., 2022; C. Zhou et al., 2022; Zhou et al., 2024; X. Zhou et al., 2022). Some previous studies have explored the plant trunk or stem diameter estimation using a vision camera (RGB-D camera or stereo camera) and deep learning methods (Sun et al., 2022; Tran et al., 2023; Xiang et al., 2020). The goal of this study was to develop a vision system that can automatically locate and measure the diameter of a citrus tree trunk. The two specific objectives of this study were (1) to train a deep-learning model to detect citrus trunks, and (2) to evaluate the trunk diameter estimation accuracy in the citrus field.

2. Materials and Methods

2.1 Image Acquisition and Labeling

324 images were collected by using a smartphone (iPhone XR, Apple Inc, Cupertino, California, United States) in a commercial citrus field in Immokalee, Florida. As shown in Fig. 1, only a single citrus tree trunk is visible in each image. Then, all images were labeled using labeling software (Roboflow software, Roboflow Inc, Des Moines, Iowa, United States), and these images were split into training, validation, and testing datasets in a ratio of 60%: 20%: 20%. Mean average precision was used to evaluate the deep learning model performance for trunk segmentation in this study.

Fig. 1. Example image of a citrus tree trunk.

2.2 Trunk Segmentation and Trunk Diameter Estimation

The YOLOv8 model can be used for object segmentation and achieves high accuracy (Jocher et al., 2023). YOLOv8 segmentation models include YOLOv8n-seg, YOLOv8s-seg, YOLOv8m-seg, YOLOv8l-seg, and YOLOv8x-seg. The YOLOv8n-seg is the lightest model that does not require much computation power and could be easily deployed on an edge device for real-time application. Therefore, the YOLOv8n-seg model was trained for trunk segmentation in this study.

Fig. 2 shows that the trunk diameter was measured around the middle of the trunk. The YOLOv8 model will segment the trunk first, and the bounding box that covers the trunk mask was used to find the middle line of the bounding box. Then the two points of intersection between the middle line and the leftmost and rightmost of the mask are selected to be the two points of injection. The distance between the two points was the trunk diameter of the citrus tree. Based on the depth information of the camera, the distance of the two injection points can be estimated. In addition, the 3D coordinates of both two injection points can be estimated from the camera, which can be used to calculate the moving direction and distance of the injection system.

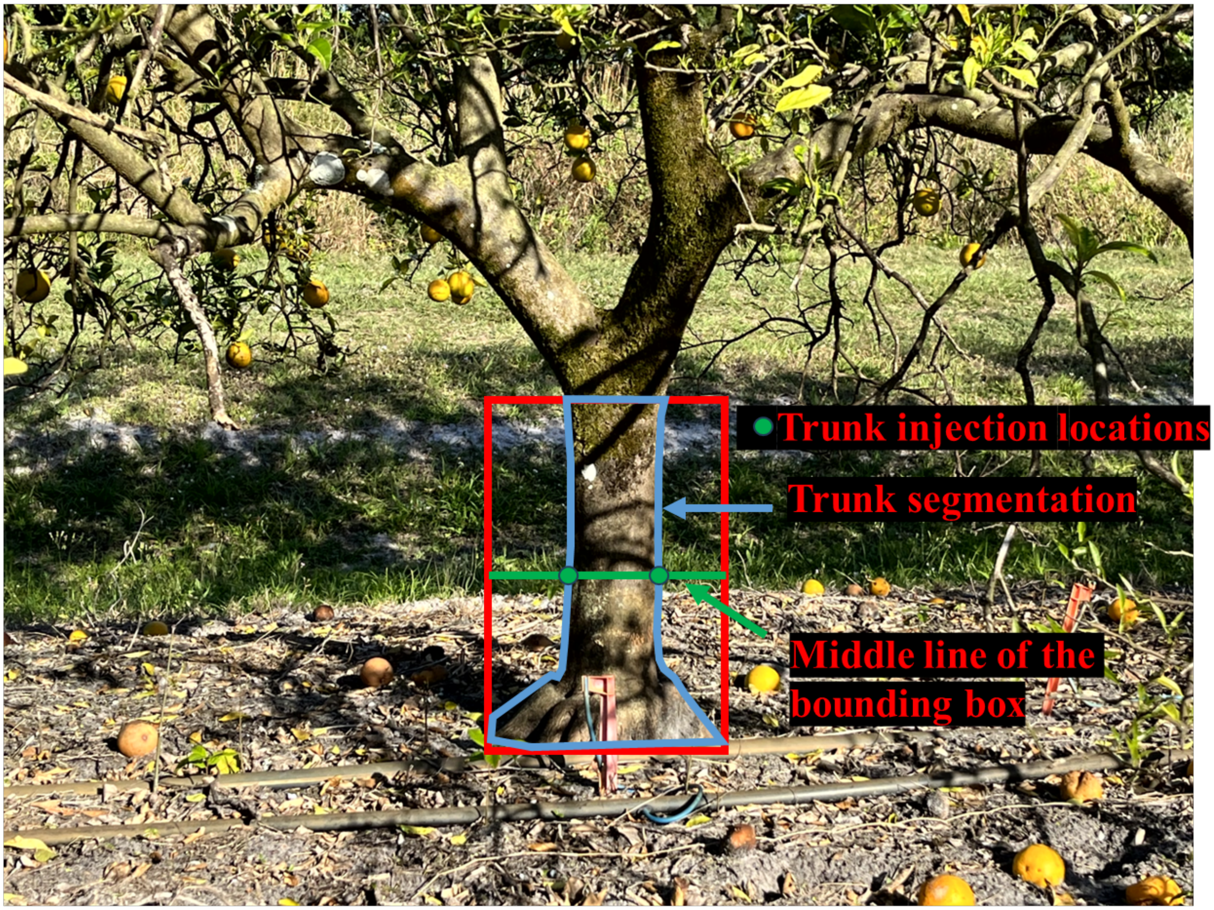

Fig. 2. Example image of trunk diameter estimation and location of the two injection points using deep learning.

2.3 Field Evaluation of the Sensing System

To evaluate the accuracy of the trunk diameter estimation, an RGB-D camera (Realsense D435i, Intel Corporation, Santa Clara, California, United States) was connected to a jetson nano to collect the RGB and depth images of the tree trunk, and the RGB image was visualized on the touch screen, as shown in Fig. 3. A total of 30 images of citrus tree trunks were collected for field testing of the sensing system. The actual diameter of each tree trunk was measured by using a digital caliper (Vernier Digital Caliper Stainless Steel 6 Inch/150mm, Qfun LLC, Shenzhen, Guangdong, China). Then, a correlation coefficient will be calculated to evaluate the accuracy of the trunk diameter estimation.

Fig. 3. Field testing of the 3-D vision sensing system in a citrus grove.

3. Results and Discussions

3.1 Tree Trunk Segmentation

Fig. 4 shows example images of trunk segmentation using the YOLOv8n-seg model. The mean average precision of the trunk segmentation was 0.99; only the segmentation accuracy of the YOLOv8n-seg model was evaluated in this study. To achieve optimal segmentation accuracy and inference speed on the Jetson nano, five different YOLOv8 segmentation models will be trained, and both testing accuracy and inference speed on the Jetson nano will be compared and evaluated in the future.

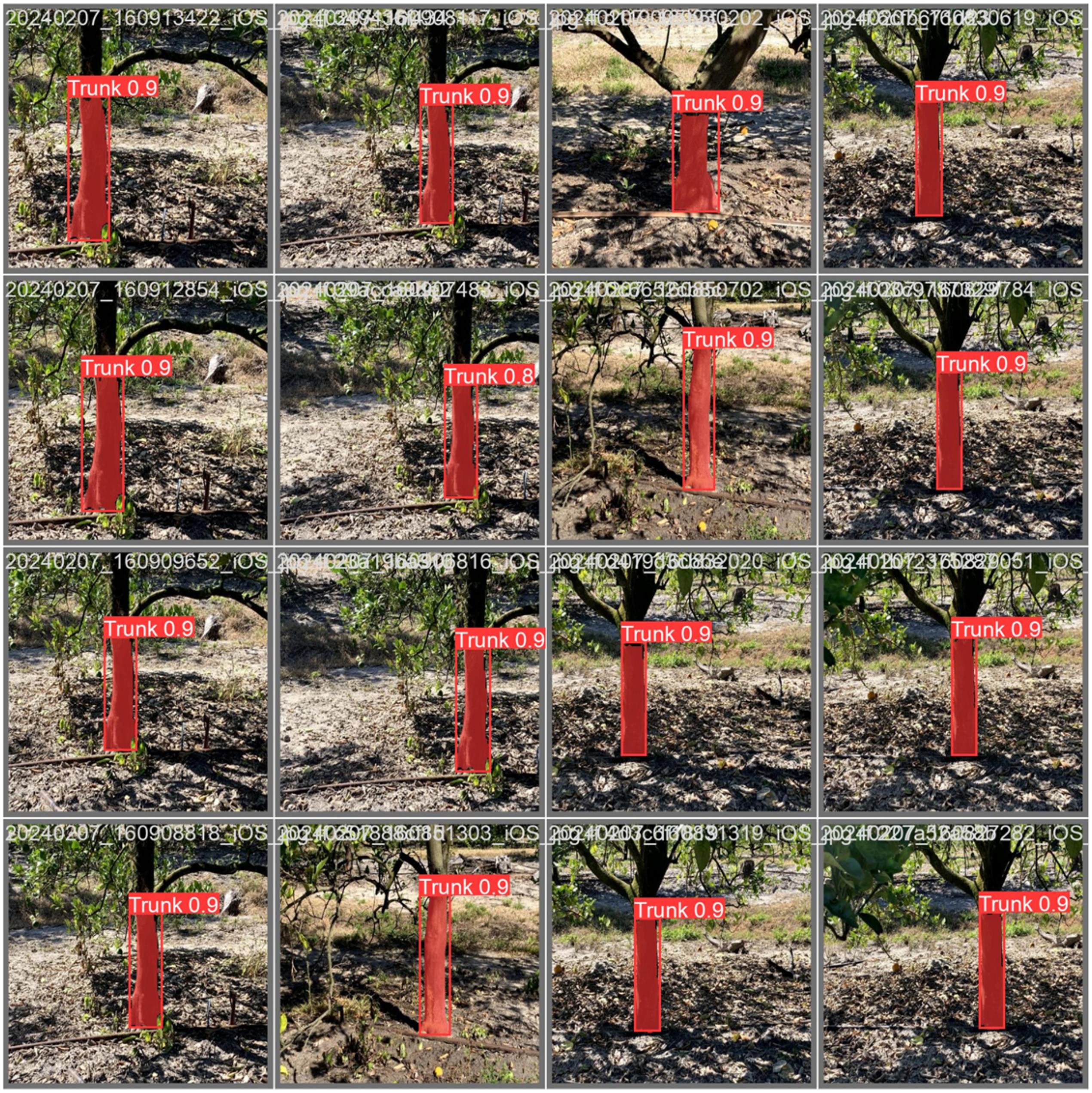

Fig. 4. Examples of trunk segmentation images using deep learning.

3.2 Field Testing

During field testing, the 3D sensing system was mounted on the needle-based trunk injection system to collect RGB and depth images of 30 citrus trunks, and the diameter of these citrus trunks was calculated using a desktop computer with an NVIDIA GTX 1080 Ti graphics processing unit. The correlation coefficient of the trunk diameter measurement from the sensing system and the ground truth was 0.91. The result shows that the sensing system can measure the trunk diameter accurately. However, only 30 citrus trees were tested in this study. To better evaluate the sensing system, more trees should be included in this study. In addition, the sensing system could provide the 3D coordinates of two injection points, which also should be evaluated. Both sensing and automation systems should be integrated, and the accuracy and efficiency of the integrated system should be tested in the future.

4. Conclusion

An AI-enabled 3D vision system was developed and evaluated for citrus trunk detection and diameter estimation in this study. The AI model achieved 0.99 segmentation accuracy, and the system accurately estimated the trunk diameter with a correlation coefficient of 0.91. This sensing system could be used to automate the needle-based injection system and improve its efficiency.

Acknowledgments

This material was made possible, in part, by a Cooperative Agreement from the US Department of Agriculture's SCRI CDRE through grant 2019-70016-29096. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the USDA. The authors would like to thank Hengyue Guan, Antonio de Oliveira Costa Neto, and Israel Ojo for their help in this study.

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