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A Prototype of an Immature Citrus Fruit Yield Mapping System

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ABSTRACT. ***Yield mapping is the first step for site‑specific crop management. Many yield mapping systems have been developed for grain crops. However, it remains a difficult task for tree crops. In this study an autonomous yield mapping system for citrus crops was developed. The system was designed to detect fruit and create yield maps at early stages so that farmers could manage the grove site specifically based on the maps. It consisted of two major sub-systems, an autonomous navigation system and an imaging system. Robot Operating System (ROS) was used for developing the autonomous navigation system on top of an unmanned ground vehicle. An inertial measurement unit (IMU), wheel encoders and a GPS were integrated using an extended Kalman filter to provide reliable navigation solutions. In the imaging system, a high‑resolution visible camera was carried by the vehicle for image acquisition. All the video frames were associated with latitude and longitude coordinates automatically. Detection of fruit from the video frames utilized a VGG16 model, which was trained with Faster-RCNN. Fruit detection was evaluated and an accuracy of 77% was achieved. The Lucas-Kanade optical flow method was used for tracking each detected fruit and counting the total number of fruit. The complete system was tested in a citrus grove in Florida.***

Keywords. *Autonomous, Citrus, Deep learning, Navigation, Robot operating system, Yield mapping*

1. Introduction

Yield mapping is considered the first step in implementing precision agriculture technologies. Yield maps can help growers better manage their farms by visualizing yield variations so that factors affecting yield would be identified easier. Therefore, projects on creating accurate yield maps using modern technologies have been conducted by researchers since 1980s. Over the years, many yield mapping systems have been developed and used for grain crops. Schueller & Bae (1987) developed a system that automatically gathered and stored combine sensor data. The system was tested when harvesting wheat, grain sorghum and soybean and yield information was generated on the combine's paths. On a similar combine system, Searcy, Schueller, Bae, Borgelt, & Stout (1989) collected data from a grain flowmeter and location detection equipment to show yield variations in the field. An analysis methodology that smoothed data was developed to create yield maps. Besides flowmeters, the other commonly used yield measurement sensor, load cells, were used by Lee, Schueller, & Burks (2005) on a wagon-based silage yield mapping system. Indirect measurement equipment, such as cameras, were also utilized for estimating grain yield. Yang & Anderson (2000) acquired color-infrared video data of grain sorghum using a

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three-camera digital video imaging system and related the data with hand-harvested grain yield at sampling sites. Significant correlations were found between grain yield and red band, green band and normalized difference vegetation index (NDVI). In general, because of the widely used mechanical harvesting equipment, the yield of grain crop can be mapped automatically in real-time.

On the other hand, estimating yield of tree corps is a more difficult work because mechanical harvesters have rarely been applied. One of the early automatic yield mapping systems for tree crops was developed by Schueller, Whitney, Wheaton, Miller, & Turner (1999) to generate yield maps for hand-harvested citrus. The individual containers of harvested fruit were mapped with the help of a GPS recorder to indicate yield variations in a citrus block. Despite that the method did not map the yield of individual trees, it was low-cost, simple and reliable. To generate more precise yield maps, Ampatzidis, Vougioukas, Bochtis, & Tsatsarelis (2009) developed a method that utilized radio frequency identification (RFID) technology to match each container's ID with individual tree's ID. Neither method used in the study solved the matching problem due to GPS signal interfacing with tree canopies. Instead of creating yield maps during harvest, detecting fruit on tree canopies to estimate yield could provide earlier yield maps. Machine vision was frequently applied for fruit detection and yield estimation. Chinchuluun & Lee (2006) and Macarthur et al. (2006) utilized color differences between mature fruit and the canopies to estimate citrus yield by count the number of fruit and associate the orange pixels with total yield, respectively. Chinchuluun & Lee (2006) created a single tree yield map for citrus for the first time. Further effort was made trying to create yield maps at an immature stage. Because fruit and leaves have very similar colors and fruit appear to be smaller at an immature stage, fruit detection becomes substantially more difficult. Multiple imaging techniques were tested for immature citrus fruit detection, including using multispectral images, hyperspectral images and RGB images (Kane & Lee, 2007, Okamoto & Lee, 2009, Kurtulmus, Lee, & Vardar, 2011). However, all these studies on immature citrus fruit were at the stage of detecting fruit. No study has been done on immature citrus yield mapping.

The objective of this study was to develop a prototype of an autonomous yield mapping system for immature green citrus fruit. Specifically, there were three sub-objectives. 1. Create an imaging platform that associates images with GPS locations automatically; 2. Train a deep learning model that can detect immature citrus fruit fast enough for real-time application; 3. Develop a fruit tracking algorithm for counting fruit numbers from videos; 4. Develop an unmanned ground vehicle platform that carries the imaging platform and provides autonomous navigation in a citrus grove.

2. Materials and Methods

The prototype of the yield mapping system had two main modules, an imaging system and a navigation system. The imaging system acquired videos, detected fruit in each video frame and counted the total number of fruit. The navigation system carried the imaging system, provided autonomous navigation in the field and recorded accurate GPS locations. These two systems were combined to associate each video frame with GPS locations to create geo-referenced data.

2.1 Imaging system

The imaging system consisted of an RGB camera (mvBlueFOX2, MATRIX VISION GmbH, Oppenweiler, Germany) and a mini computer (mini-ITX, Clearpath Robotics, Kitchener, Canada). The computer utilized a pre-trained deep learning model for detecting fruit in each of the video frames acquired by the camera. It also tracked the detected fruit in the entire process to avoid counting the same fruit multiple times.

2.1.1 Fruit detection using a deep learning model

Fruit detection for a real-time yield mapping system must achieve high accuracies and fast processing time. To meet these requirements, the Faster R-CNN was used to train a VGG16 model. The VGG16 model was originally trained for ImageNet. Its performance had been proved by achieving a 70% accuracy on ImageNet classification tasks. Faster R-CNN is the state-of-the-art object detection network, which achieved the fastest speed by using a so-called region proposal network (RPN). Therefore, combining a VGG16 model with Faster R-CNN network was tested in this study.

Images were acquired in 2016 in a citrus grove at Citra, Florida. From later May to early November, 1184 images of citrus canopies (variety: Hamlin) were acquired. The images had a spatial resolution of 5184 × 3456 pixels. To prepare the dataset for training a VGG16 model using Faster R-CNN, fruit in all the images were labeled, and the locations of fruit were stored in a text file. Figure 1 shows an example image with fruit being labeled. A total of approximately 40,000 fruit locations were generated. The images were divided into training, validation and testing sets with a ratio of 0.35, 0.35 and 0.3, respectively. The training took 50 hours to converge to the final model, starting from a pre-trained ImageNet VGG16 model. The process was named transfer learning, which fine-tuned the parameters in the pre-trained model for the new classification task.

Figure 1. An example image of an immature citrus canopy with all the fruit labeled using red rectangles.

2.1.2 Fruit tracking and counting

To use the trained VGG16 model for detecting fruit and counting fruit numbers, a tracking algorithm was written using Python. The algorithm found the most prominent corner feature around each detected fruit and applied Lucas-Kanade optical flow method to track the motions of the corners. Locations of each fruit in the next frame were estimated based on the tracked motions. In the next frame, if the location of a newly detected fruit overlapped with an estimated fruit location from the previous frame, it would not be added to the total number. For instance, 40 oranges were detected in frame 1, and 30 of them appeared in frame 2. The locations of the 30 oranges in frame 2 would be estimated from the optical flow method. The true locations of those 30 oranges would be detected and compared to the estimated locations. If those locations overlapped, the 30 oranges would be added for counting total number of fruit.

2.2 Navigation system

The navigation system was developed on the basis of an unmanned ground vehicle (Husky, Clearpath Robotics, Kitchener, Canada). Sensors used for navigation included a GPS, an inertial measurement unit (IMU), wheel encoders, a LiDAR (UTM-30LX, Hokuyo Automatic CO., Ltd, Japan) and a Kinect (Kinect v2, Microsoft CO., WA, USA). The navigation included two modes, navigation in an open field and navigation in a citrus grove. The entire navigation algorithm was developed using Robot Operating System (ROS) under the Ubuntu Linux system.

The first mode, navigation in an open field, created a graphical interface and allowed to open a georeferenced map and set navigation goals by clicking on the map. The vehicle would run from its current position to the destinations one by one while avoiding all the obstacles on its way. In this mode, the GPS, the IMU and the wheel encoders were fused using an extended Kalman filter to improve reliability and accuracy of localization (Figure 2). The Lidar was integrated to achieve the simultaneous localization and mapping (SLAM).

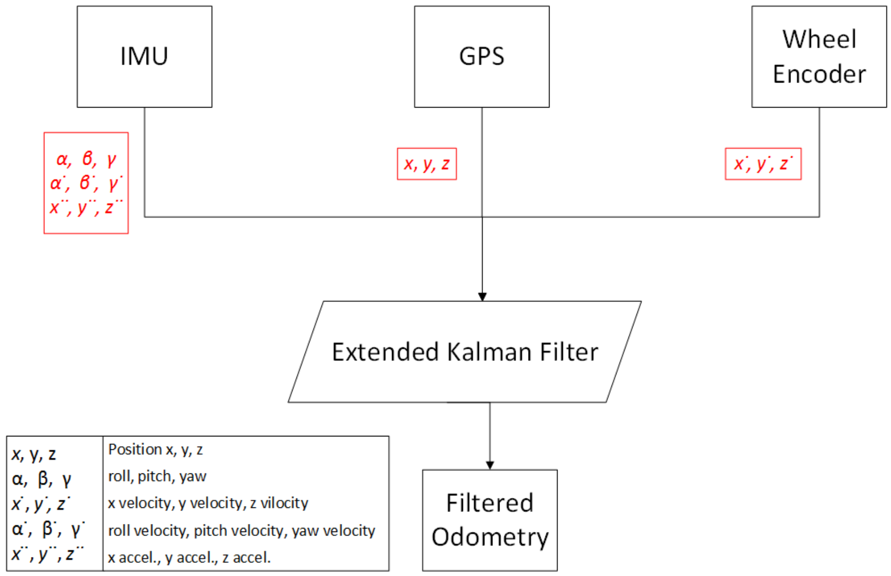

Figure 2. Fusing GPS, IMU and wheel encoders using an extended Kalman filter.

The second mode, navigation in a citrus grove, utilized the video streams from the Kinect to automatically assign navigation goals so that navigation between two rows of trees could be autonomous. The upper edges of tree canopies were detected and were used for estimating the relative positions and orientations of the vehicle. Then the relative positions and orientations were used to calculate navigation goals. After the navigation goals were set, the system utilized SLAM to drive.

2.3 Remote communication and monitoring

A ROS network was established for communication between the vehicle and a remote workstation. It allowed to monitor the data from all the sensors including images from cameras remotely. It also allowed commands to be sent to control every aspect of the system manually.

A ROS library named Mapviz was used for real-time data monitoring and visualization. It created a graphical interface in which data such as geo-referenced map, GPS coordinates, laser scans, live video streams, etc. can be displayed. An example is shown in Figure 2, which shows a map of a citrus grove in Citra, Florida, the path of the vehicle as a series of GPS coordinates, images from the RGB camera and the Kinect, as well as the total number of fruit counted by the imaging system.

3. Results and Discussions

The mean average precision of the fine-tuned VGG16 model on testing images was 77%. Example images with fruit been marked are shown in Figure 3. Figure 3a shows an early stage of a citrus canopy and Figure 3b shows a later stage of a citrus canopy. Based on visual observations, detection precisions at later stages were higher than that at early stages.

The average speed for processing each image was 0.25 second, which converted to 4 frames per second. The speed was based on an Intel 7th generation CPU (Intel Core i7-7920HQ) and a Nvidia's 8 GB GPU (Nvidia Quadro P4000 w/8GB GDDR5). Although the speed was not fast enough to keep up with the camera's frame rate, which was 30 frames per second, it was fast enough for real-time detections.

The tracking and counting algorithms have also been tested using recorded videos. The algorithm could successfully detect fruit in each video frame, tracking the fruit and eliminate multiple counted fruit. However, the final accuracy of the tracking algorithm remains for evaluation.

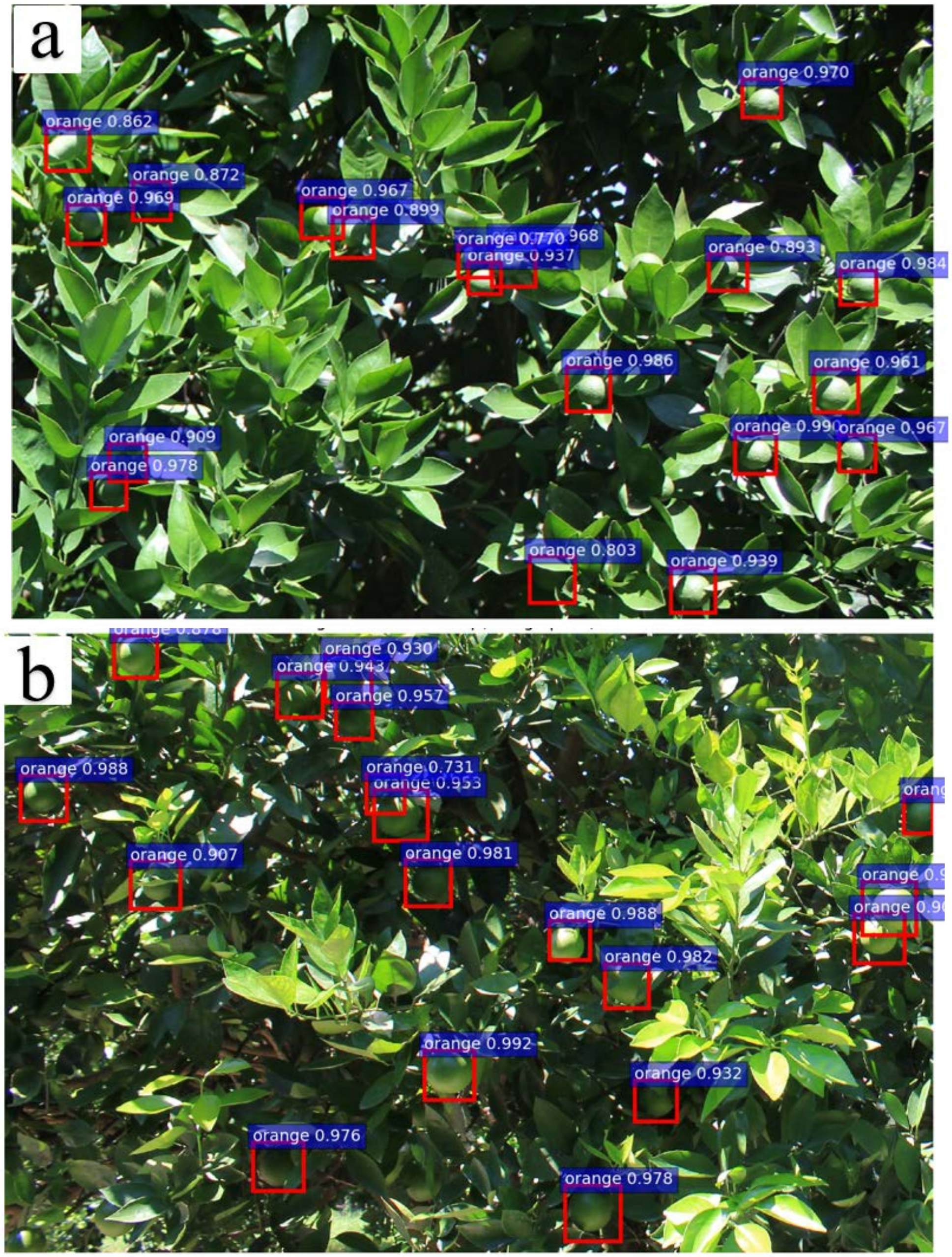

Figure 3. Example images of citrus canopies with fruit detected: (a) early citrus canopy in late May, (b) later stage of citrus canopy in August.

The autonomous vehicle was tested in an open field for evaluating localization accuracy. Seven runs were conducted by setting seven different navigation goals on a geo-referenced map. The goals were represented as GPS coordinates. While the vehicle stopped at each navigation goal, it collected 50 GPS data and computed the mean value as its true GPS coordinates. The error was calculated by comparing the true GPS coordinates with the set goal. Table 1 shows the error of the seven runs. A mean error of 0.43 meters was achieved.

Table 1. Localization accuracy of the vehicle in seven runs using extended Kalman filter.

	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Mean error
Error (m)	0.27	0.41	0.38	0.49	0.56	0.29	0.61	0.43

The navigation in a citrus grove was simulated using a simulation program named Gazebo and tested in the field. The robot could successfully run from the beginning of a row to the end of the row and stay close to between trees. However, algorithms for turning the robot at the end of each row need to be developed as a next step.

4. Conclusion

The prototype of an immature citrus yield mapping system developed in this study achieved most functions of the intended final product. The imaging system acquired RGB video streams, detected fruit and counted the total number of fruit in real-time. The detection accuracy using individual images achieved 77% at various conditions, including different growth stages, different illumination conditions and different occlusion situations. The processing speed achieved 0.25 second for each video frame. The navigation system could carry the imaging system and achieve autonomous navigation both in an open field and in a citrus grove. Remote communication and control was established, and user-friendly graphical interfaces were created. However, both imaging system and navigation system need to be improved in the next step. For the imaging system, one more RGB camera and a thermal camera will be utilized for combining RGB and thermal information. The two imaging sources will be fused for a better detection accuracy. The final accuracy of real-time detection and counting will be evaluated by comparing the generated yield with real yield after harvest. For the navigation system, algorithms will be developed to allow the vehicle to turn at the end of each row in the citrus grove.

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