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IFAC PapersOnLine 55-32 (2022) 124–128

Canopy Density Estimation of Apple Trees

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Abstract: Tree canopy density is an important parameter in developing a decision support system for precision orchard management including application of the right amount of nutrients at the right time and right location. Previous studies mostly focus on canopy characterization using the light detection and ranging (LiDAR) sensor which lacks critical color and texture information. This study utilized a ground-based stereo-vision sensor mounted on a utility vehicle to capture the canopy data during the growing stage (July, 2021) in a commercial orchard. The acquired color images, along with the point-cloud data, was used to segment out individual trees and estimate canopy density which is the measure of canopy cover per unit total area for each tree. A K-means segmentation method followed by depth thresholding was used to segment the desired tree canopies. The segmentation was compared to the manual segmentation and a F_1 score of 0.78 was obtained. The density was obtained using the ratio of pixel count of vegetation and total area of interest around the trunk of specific trees. The obtained result was compared against the expert's assessment of tree vigor (categorical variable with values from 1 to 5), which showed a good correlation ($R^2 = 0.81$). The obtained canopy density, along with other parameters including trunk size, and canopy color change during fall, will be used in the future to develop a decision support system for the assessment of nutrient requirement for individual trees to achieve the plant level precision nutrient management.

Keywords: Canopy density, canopy segmentation, agricultural automation, machine vision, canopy characterization

1. INTRODUCTION

The canopy characteristics of a tree can be helpful during decision making in various orchard operations such as fertilization, pruning, irrigation and spraying (Torres-Sanchez et al., 2018). Traditionally, without information on canopy characteristics, it is difficult to make informed, objective farming decision, which may lead to higher probability of over or under application of farming inputs (e.g. water and nutrients). This, in turn, negatively impacts fruit yield and quality. Information on different canopy parameters of a tree-including canopy width, height, density, volume, and leaf color, can be important for growers to make more informed, and less-subjective farming decisions. This can help growers manage individual trees to achieve their highest potential.

There are numerous studies on ground-based systems for canopy characterization. One group of studies use Ultrasonic sensor-based techniques (Nan et al., 2019; Tumbo et al., 2002), whereas Light Detection and Ranging (LiDAR) sensor-based techniques have been used by a large number of other studies e.g.(Hu and Whitty, 2019; Mahmud et al., 2021; Chakraborty et al., 2019; Bargoti et al., 2015; Mahmud and He, 2020). There are also some studies in recent years based on aerial imagery using UAV (Sun et al., 2019; Torres-Sanchez et al., 2018) and ground-based stereo vision techniques (Dong et al., 2020).

While LiDAR is the most commonly used sensor for canopy characterization, it is generally more costly, has lower spatial resolution (lower density 3D points; Broggi et al. (2013)) and lacks inherently registered color and texture information. Canopy characterization using UAVs performs well in terms of a quick analysis for a larger plot, but fails to give important parameters at the individual tree level. Lower cost stereo-vision sensors, which can provide co-registered color and 3D information at a desirable

10.1016/j.ifacol.2022.11.126

resolution, can be a viable alternative to LiDAR and aerial methods of data collection. The choice between stereo-vision and LiDAR-based sensors is also an open question in the autonomous driving industry where both systems have their own advantages and disadvantages.

A previous stereo-vision based study (e.g. Dong et al., 2020) focused on tree reconstruction and estimated canopy height and volume for trees that are clearly separated. This study makes use of a stereo-vision camera to segment the tree in a more complex natural orchard environment and calculate the denseness of vegetation in the tree canopy per unit total covered area, also referred to as tree canopy density. As tree canopy density is correlated with tree nutritional status (Tumbo et al., 2002), canopy density along with other parameters such as leaf color, trunk width, shoot length, and canopy volume can be used in estimating reliable nutrition recommendations for fruit trees.

2. MATERIALS AND METHODS

2.1 Data Collection and Equipment Setup

The data used in this study was collected in July 2021 in a commercial Jazz orchard (Yakima Valley Orchard, Prosser, WA). A total of sixteen rows with 172 sample apple trees were imaged and analyzed. The trees were trained to a vertical trellis system creating a planar (2D) architecture.

The images were collected using a Zed camera (Stereolabs, Paris, France) (Figure 1b) installed on a utility vehicle (John Deere, Moline, Illinois) (Figure 1a). The imaging system captured stereo-pair images at a resolution of 1242 x 2208 pixels, which were then processed using a stereo-vision technique to estimate the disparity and depth values for each pixel. The system uses neural networks to identify a number of key-points in each image to find disparities and triangulate the points for depth estimation (Stereolabs (2019)). Images were taken from the moving vehicle 1.5–2 m to the tree trunk so that the entire canopy was visible in a single image. The data was recorded in natural lighting conditions in the form of a SVO file , which contained all metadata for the frames. The frames containing the tracked trees were manually noted and extracted later during processing.

(a) (b)

Fig. 1. Data collection system–a) utility vehicle with the image acquisition setup and b) Zed2 camera used in this experiment (Stereolabs, France)

2.2 Image Processing and Density Estimation

The Zed python API was used to extract the depth and RGB images of each frame containing specific sample trees. A k-means clustering with two clusters was applied to separate the visible sky from the vegetation in these images as the sky had a clearly different color from the vegetation. After the separation of the background sky, a depth threshold at eighty-five percentile was used to get rid of the background trees (trees in rows behind the target row). A dynamic (percentile-based) depth threshold was used over a fixed threshold as this would adapt to the difference in depth of the trees from the imaging system and since the majority of the pixels were occupied by the foreground/target tree canopy. After the foreground tree canopy was segmented, a fixed size rectangle of 850 x 2058 pixels was fitted to each tree so that the area around the trunk of the tree was covered and not affected by branches from neighboring trees. The fitted rectangle was used to calculate the canopy density for each tree using 1

$$\text{Canopy Density } = \frac{\text{Pixels occupied by vegetation}}{\text{Total number of pixels}} \quad (1)$$

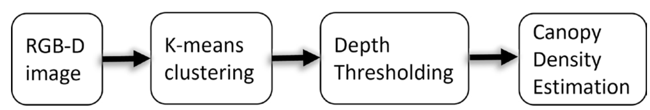


Fig. 2. Data collection and image processing flow

2.3 Performance Assessment

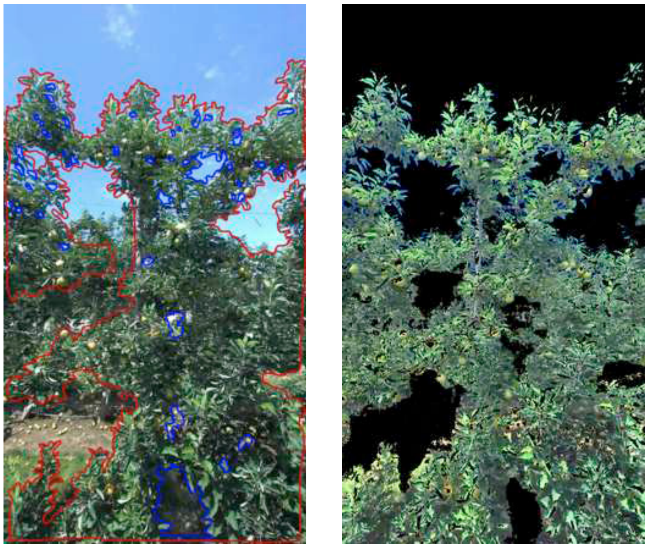
The segmentation of the tree in the foreground from the background was evaluated using a manually segmented image. For manual segmentation, a red boundary was drawn on the outside boundary of tree canopies and a blue boundary was drawn for the holes within the canopies (Figure 3a). The foreground mask was obtained by subtracting holes from the outside boundary. The result from the segmentation algorithm (Figure 3b) was compared against the mask created from manual labelling. Performance was evaluated using Precision, Recall and F1 matrices which are defined in equations 2, 3 and 4 respectively.

$$\text{Precision } = \frac{\text{True Positive}}{\text{True Positive + False Negative}} \quad (2)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive + True Negative}} \quad (3)$$

$$F_1 = 2 * \frac{\text{Precision*Recall}}{\text{Precision + Recall}} \quad (4)$$

As an estimate of the canopy density, an expert, a grower with more than thirty years of experience, was asked to participate during data collection and rate the trees on a scale of 1 to 5, 1 being lowest vigor and 5 being the most vigorous, twice–so that any bias would be averaged out. The canopy density of the tree can be related to the vigor of the tree or the amount of growth the tree has. The vigor ratings were based on the visual assessment of the shoot growth throughout the tree. This data was used as a ground truth to compare the performance of the density estimation algorithm.



(a) (b)

Fig. 3. a) Manually; and b) Automatically segmented images for a sample tree. In Fig a), the red line represents the outside boundary and blue line represent inside boundaries

3. RESULTS AND DISCUSSIONS

3.1 Segmentation Results

The images were segmented using techniques discussed in section 2.2. A sample tree with results at different stages of segmentation is shown in Figure 4.

The final segmentation result for a sample tree is shown more clearly in Figure 5. The algorithm was not affected by the variation in natural lighting condition. The parts in yellow are labelled as foreground in the manual segmentation and as background in the automatic segmentation whereas the part in blue is segmented as background in manual segmentation and foreground in automatic segmentation.

The confusion matrix for the segmentation of thirteen trees is shown in Figure 6. True positives and true negatives are the parts correctly identified as foreground and background in both segmentation (gray areas in Figure 5). False positives are the part of the background that has been falsely identified as foreground (blue parts in Figure 5 section A2) and a false negative is a part of the foreground that has been falsely labeled as background in automatic segmentation (yellow parts in Figure 5, section A1).

We can see from Figure 3 that the manual segmentation boundary is not exact and has some padding on the edges as can be seen clearly in Figure 5, section A1. We can see from the confusion matrix (Figure 6) that false negative is a larger issue, most of which were likely caused by padding and therefore, can be justified. With the proposed algorithm, we obtained precision of 0.82, recall of 0.75 and a F_1 score of 0.78. With the proposed algorithm, we were able to segment the foreground tree in a natural environment. Moving forward, the results from this study can be helpful in subsequent studies for canopy characterization.

3.2 Density Estimation

After the segmentation of the trees into foreground and background, the density of each sample tree (within the corresponding bounding box) was estimated using equation 1 as discussed earlier in section 2.2. The resulting canopy density ranged from 0 to 1 for each tree. Canopy density was compared to the canopy vigor estimation of the expert as discussed earlier in section 2.3 (Figure 7). The results from density estimation were on a continuous scale (0-1) and that of the expert's assessment was on a discrete scale (1-5), so the median values of the density in each of the discrete value of expert's assessment were used for the linear fitting of the data. An R^2 value of 0.814 was

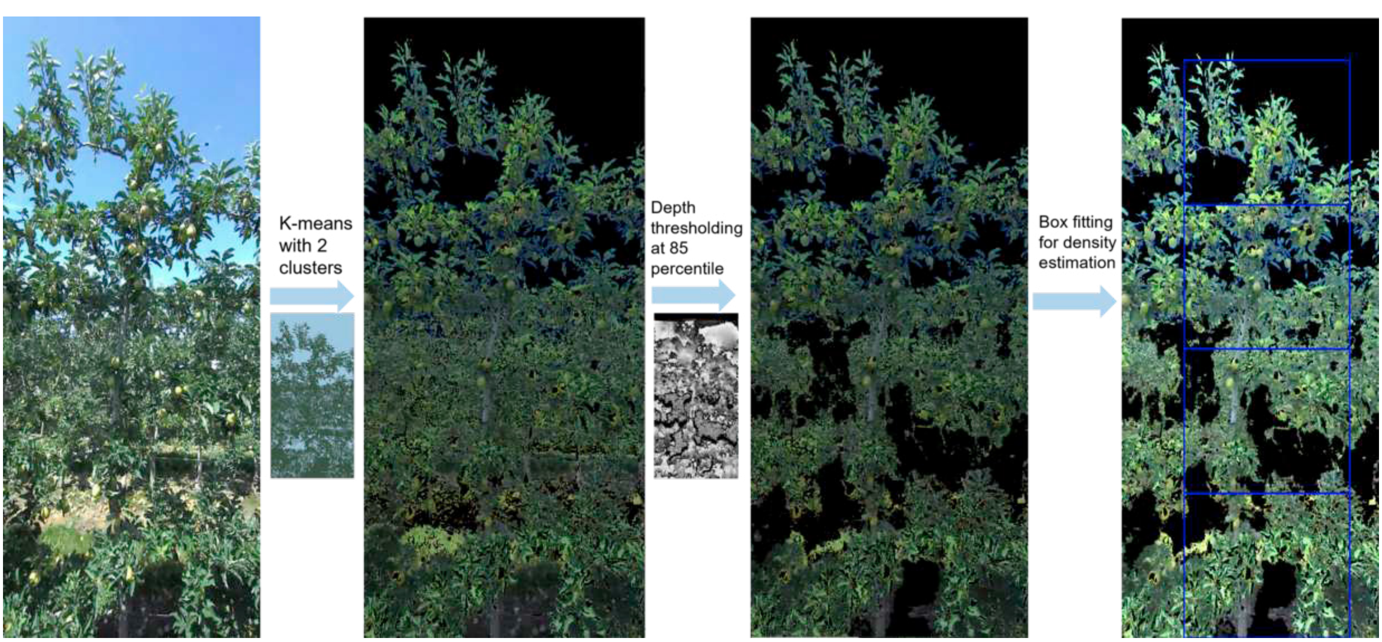


Fig. 4. A sample tree with results at different stages of segmentation.

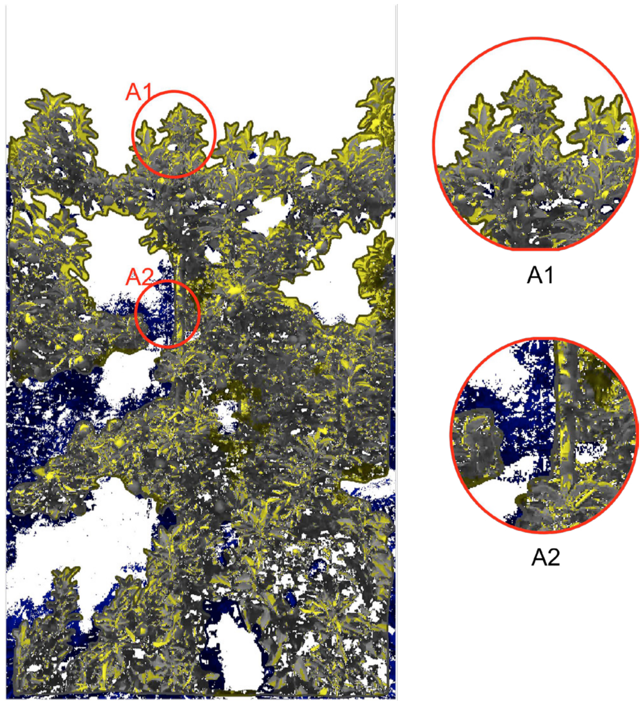


Fig. 5. Segmentation results (blue) comparison with ground truth (Yellow). Gray color represents portions present in both.

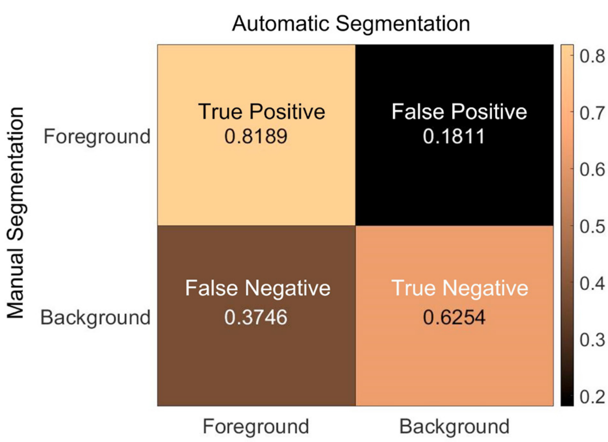


Fig. 6. Normalized confusion matrix for the segmentation

found between the estimation from the proposed method and the vigor estimation given by the expert.

4. CONCLUSIONS

This study focused on segmenting out apple tree canopies and estimating their canopy density in a natural orchard environment. A stereo-vision system was used to collect and process canopy images. The segmentation method used in this study achieved an F_1 score of 0.78. Discrepancies between automatically estimated and ground truth canopy areas were primarily caused by inaccuracies in manual labeling of the canopy images as ground truth data. The preliminary results of canopy density measure from the study showed a good correlation ($R^2 = 0.814$) with the expert assessment of the vigor of the tree. We are planning to conduct a more comprehensive analysis

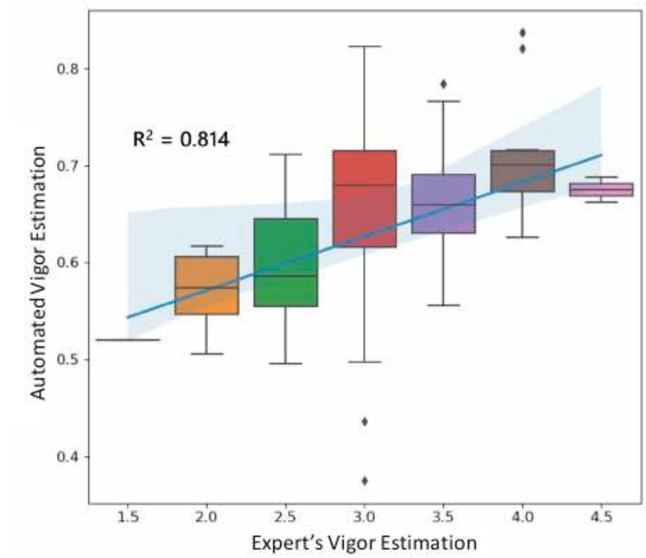


Fig. 7. Relationship between automated canopy density estimation and expert's estimation of canopy vigor.

with more experts involved to eliminate any bias in the assessment of tree.

With a stereo-vision based system, and color and depth images, different parameters can be found to characterize the canopy which will be helpful for different orchard operations. In the future, the canopy density information will be used along with other canopy parameters like trunk diameter, shoot length, and leaf color to develop a decision support system for recommending nutrient amount for individual trees.

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