Engineering, Structures and Innovations

Scot Langolis

Section Editor

Comparison of Manual Inventory Counts to an Automated Approach Using an Unmanned Aerial System

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Index words: nursery inventory, OBIA, UAS, Feature Analyst

Significance to the Industry: Collection of plant inventory data is time consuming, often inaccurate, and costly. Although improvements have been made to the process, it still relies heavily on manual methods. The long-term objective of this research program is to develop an automated method to collect and process inventory data using aerial images. This experiment is focused on comparing the traditional manual counting of plants to an automated approach using an unmanned aerial system (UAS) and image processing software under nursery conditions. In all cases the manual counting method took less time compared to the automated approach. Counts generated by the software ranged from 86 to 118% of what nursery employees counted as 'salable'.

Nature of Work: In general, the nursery industry lacks an automated inventory control system (2). The process of collecting inventory data in a nursery is labor intensive involving the physical counting of thousands of plants. Due to the time involved in manually counting plants, growers often count only a portion of their crop (1). Aerial images combined with image processing software have been used in agricultural and environmental applications. Since nurseries grow a wide range of plants, this may require several counting programs (algorithms). This study was designed to compare, under nursery conditions, a manual counting method to an automated approach. Research was conducted at McCorkle Nurseries, Inc., Dearing, GA on 1 May 2015. Sections within four outdoor container production blocks were used. Section #1 (48' x 52') was *Miscanthus sinensis* Anderss 'Adagio' growing in #3 containers: typical plant size was 33 inches wide by 17 inches tall. Section #2 (46' x 76') *was Ilex crenata* Thunb. 'Helleri' growing in #3 containers: typical plant size was 20 inches wide by 12 inches tall. Section #3 (30' x 76') was *Abelia* R. Br. x 'Rose Creek' growing in #3 containers: typical plant size was 15 inches wide by 12 inches tall. Section #4 (27' x 56') was *Rhaphiolepis* Lindl. Spring Sonata™, growing in #3 containers: typical plant size was 14 inches wide by 10 inches tall. For all blocks, containers were positioned on black polypropylene ground cover.

Data collection:

a. Aerial images were obtained using an eight bladed (coaxial) UAS (Fig. 1a) assembled using electronic components from HiSystems GmbH (Moomerland, Germany). Two cameras (Fig. 1b) were mounted to the underside of the UAS. Cameras were not mounted on a pitch and roll compensated gimbal so horizontal positioning was controlled by the pilot. Both cameras were programmed to take images automatically every 5 seconds. The ‘normal’ camera was a Canon (Melville, NY) PowerShot SX260 HS (12.1 MP; lens focal length 4.5 (W)-90 (T) mm. The ‘near infrared’ (NIR) camera was the same make and model of Canon with the optics modified (LDP, LLC, Carlstadt, NJ) where the red channel is the near-infrared from 680 nm to 880 nm and both blue and green channels were visible bands. The UAS was positioned over the center of every section at approximately 85’. Image spatial resolution was calculated based on 7.9 inches square white boards positioned at the corners of sections, resulting in 0.20 to 0.26 inches/pixel. The amount of flying time was recorded when the UAS lifted off the ground and then landed. A subjective estimate of cloud cover was determined to be less than 5% and a ground wind speed (0-2.5 miles/h).

b. The same sections of plants were counted manually by nursery personnel that typically collect inventory data. Manual counts of ‘salable’ plants were made just minutes after aerial images were taken. The amount of time required to count blocks was recorded. For *Abelia*, *Miscanthus*, and *Ilex*, only one count was performed; for *Rhaphiolepis* two workers counted the same block and the final time and count represents an average.

Algorithm training using Feature Analyst® (FA) (Overwatch System Ltd. Austin, TX): Two images (‘normal’ and NIR) from each plant section were used to train a total of eight algorithms. The general process of creating the algorithms is the same as described in (3). Parameters used to create the algorithm were based on user experience and a subjective analysis of the output files after procedures were applied. Figure 2 illustrates a visual output of counting performance using FA for ‘normal’ and NIR images.

Results and discussion: The purpose of the experiment was to assess, at this point in time, how an automated plant counting system (using a UAS to collect images and processed using one commercial software image processing software) compares to a manual plant counting method (Table 1).

Count accuracy:

Counts generated by the automated approach (UAS to collect images that are analyzed using Feature Analyst) varied from an under-count (e.g. 86% for *Abelia* using a normal image) to over-count (e.g. 118% for *Rhaphiolepis* using a NIR image) depending on species and type of camera (normal and NIR).

Counting time:
For these small test blocks the manual counting was always faster than the automated approach. The time for the UAS to take-off, collect an image, and return to the ground (approximately 2 minutes) was longer than the time for inventory workers to count these small blocks. The time to process images by a well-trained person added an additional 7 to 12 minutes.

There are many differences between this study and previous work by these authors. Previous experiments used ‘constructed’ plant blocks designed to evaluate such factors as plant spacing, presence of flowers and effect of ground cover type on counting accuracy. This study used container-grown plants ‘in situ’. Previous research differed in that the flight altitude was lower (72 ft versus 85 ft) and camera resolution was higher (24.3 MP versus 12.1 MP). For this experiment the unmanned aerial system was configured with dual cameras to evaluate if images taken under the same conditions (i.e. light, altitude) but different wavelengths could improve processing results when using FA. It is difficult to determine from our results whether a NIR image will significantly improve count accuracy compared to a normal image, therefore, this issue needs to be studied further.

An unexpected outcome when using ‘in situ’ production blocks was what nursery employees count. For example, in the *Ilex* ‘section’ the nursery employee counted 251 ‘total’ plants of which 6 were identified as ‘unsalable’ (i.e. 245 ‘salable’). We observed only one ‘dead’ plant (i.e. brown foliage). After discussion within the group, we determined that the nursery employee was making a subjective grade determination; ‘unsalable’ plants had green, healthy foliage but were poorly rooted, poorly shaped (Fig. 3) or were totally dead (brown foliage). The image processing software could not discriminate quality issues and could only separate dead plants (brown foliage) from plants with living foliage.

At first glance, based on time and count accuracy results from a comparison of counting methods, a manual method would be preferred, however, the block sizes in this experiment were small, thus favoring the traditional counting method. As the production area increases (i.e. number of plants), it is possible an automated approach similar to what was investigated here might prove useful. Future work should focus on comparing counting methods using blocks of various sizes. Image analysis was based on the training of new algorithms for every image and block of plants of interest, however, future approaches could use a library of existing algorithms that could decrease the time spent analyzing images.

Acknowledgements: The authors thank Skeetter & Chris McCorkle and Brian Jernigan (McCorkle Nurseries, Dearing, GA) for their assistance with this project.

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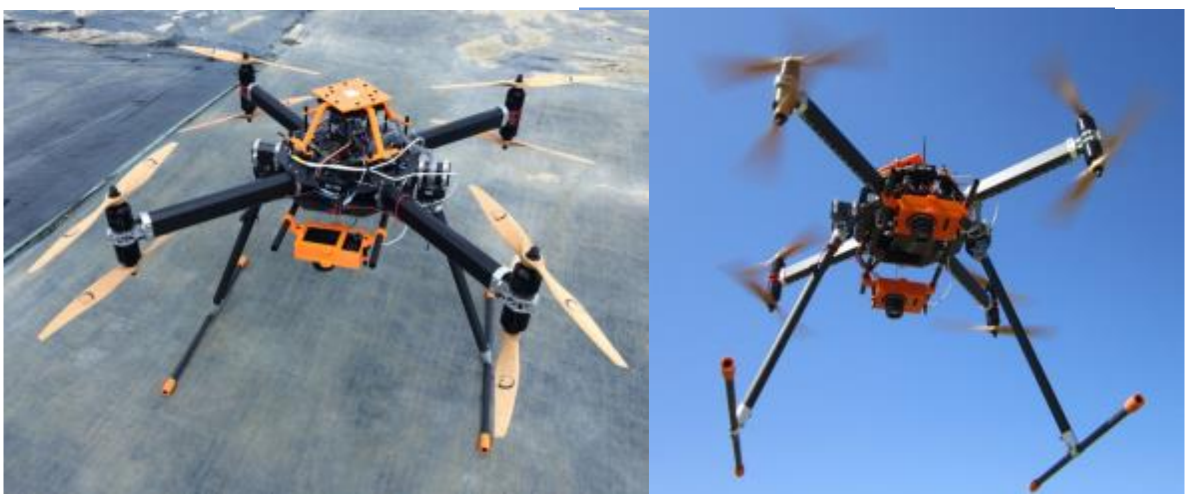

(a) (b)

Fig. 1. (a) UAS; (b) Canon PowerShot cameras mounted on underside of frame

Fig. 2. Output image for a 'normal' (left) and NIR (right) image of the *Miscanthus* section. An option in Feature Analyst is for the software to place a visual mark (yellow dot in this example) on every object counted.

Fig. 3. Example from the *Ilex* section of what the nursery employee determined to be 'salable' (right) and not salable (left). From an aerial image Feature Analyst counted both as 'salable'.

Table 1. Comparison of count accuracy and time required to count four container-grown plant sections at McCorkle Nursery on 1 May 2015 using two different methods.

		Counts		Time		
Plant	**Image Type**	Nursery manual, 'saleable'	Automated (% of nursery 'salable')	Nursery manual, 'salable'	UAS - obtain aerial image	Software processing[z]
Rhaphiolepis	normal	542	555 (102%)	1 min	2 min 15 sec	12 min
Rhaphiolepis	NIR	542	639 (118%)	1 min	2 min 15 sec	12 min
Ilex	normal	245	218 (89%)	1 min 40 sec	1 min 50 sec	9 min
Ilex	NIR	245	220 (90%)	1 min 40 sec	1 min 50 sec	8 min
Miscanthus	normal	126	119 (94%)	45	1 min 50 sec	12 min
Miscanthus	NIR	126	120 (95%)	45	1 min 50 sec	7 min
Abelia	normal	199	183 (92%)	1 min 34 sec	1 min 45 sec	9 min
Abelia	NIR	199	197 (99%)	1 min 34 sec	1 min 45 sec	11 min

[z]Time required to analyze images using Feature Analyst®