APPLICATIONS OF SMALL UAV SYSTEMS FOR TREE AND NURSERY INVENTORY MANAGEMENT

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ABSTRACT

Unmanned aerial vehicles (UAV) systems could provide an 'as needed' solution for small-to-medium scale farmers who want to monitor their fields at a low altitude with high accuracy frequently. This paper highlights the application of UAV systems in container counting and tree counting, which is vital to predict the tree density and yield. The main challenge of plant counting comes from the severe overlap of adjacent plants. In this paper, two types of crops were discussed. One crop is with uniform canopy area (e.g. container plants and citrus trees) and another is with non-uniform canopy area (e.g. Christmas trees). For the first type, aerial images of container-grown plants with green and yellow foliage were acquired with a stable, ground-based boom truck and UAV system. Two different index sets, (2*G-R-B) and (R-G)/(R+G) were used to extract the green and yellow container plants from background, respectively. A counting algorithm based on average canopy area was developed to estimate plant count. The effects of shoot height and adjacent plant distance on the accuracy of the algorithm are discussed. Further, the algorithm was successfully applied on the panorama images created from video file using Microsoft ® ICE software. In this realistic case, there are about 22,000 plants in the image and the applied algorithm accurately predicted the 22,000 plants within ±5%. This also indicates that the algorithm was successful when applied to low-resolution images. In addition, a second algorithm was employed which counted plants based on the local maximum value at or near the center of coniferous tree. A 3-D intensity distribution of the images showed that local maximum of intensity of (R-G) matched well with tree centers. Also, minimum distance filter (MDF) and thresholds generated from color component histograms were successfully used to remove the falsely identified tree locations.

Keywords: Tree inventory management, tree counting, UAV system

INTRODUCTION

Tree inventory is a diverse research topic which mainly focuses on four aspects: species (GENTRY, 1988; Williams-Linera, 2002), physical parameter (including size, diameter and height) estimate (Næsset, 2001; Popescu, 2003), plant health (G. Sepulcre-Cantó, 2006; Sankaran, 2013) and total number of the plants. In this paper, we will target our research to tree and nursery number inventory management. Research herein will focus on measuring crop inventory using an UAV platform, in which researcher will provide an accurate count of field and container grown plants.

Plant inventory management still primarily involves manual counting. Manual management is labor-intensive and time consuming, especially for orchards and nursery fields with large areas. Due to the time involved in manually counting plants, growers often count only a portion of their crop (Hale, 1984). Manual counting also prevents producer access to real-time inventory. Variation in worker skill level and data collection also results in variable accuracy. When the aforementioned errors are compounded it can result in infrequent, inaccurate plant counts.

Remote sensing provides the capability to conduct crop management in a non-contact way and in real-time. Applying remote sensing technology on tree identification and counting has focused on two directions: One is LIDAR or Laser scanning, which can be not visualized directly. JANG (2008) used airborne Lidar data to retrieve the raster height image of apple tree groves. Jang then applied the local maximum and region growing to delineate individual trees. Similar research was conducted by Pouliot (2004) on tree crown detection and delineation based on local maximum using digital camera images. Alternatively, others have approached identification of plants using visible aerial images. Karantzalos and Argiales (2004) used an anisotropic diffusion filter and local spatial maximum of the Laplacian to detect well spaced, individual olive trees. Robust counting results were obtained for olive trees with non-overlapping canopies. Camargo and Mirando (2009) developed an approach to identify, count, and estimate canopy diameter of citrus trees within QuickBird satellite images. A k-means algorithm was used to extract the tree region before utilizing a generic algorithm to adjust the tree position to the tree center and estimate canopy diameter. An overall accuracy of approximately 93% was achieved under conditions of low/high tree row space and uniform/non-uniform tree size.

Although remote sensing has proved to be an efficient method in many agricultural applications, a suitable choice for aerial platforms is important since it is closely related to resolution, monitoring accuracy, time and subsequent cost. Grenzdörffer (2008) pointed out that high temporal resolution images are difficult and costly to obtain, either by satellite imagery or by conventional airborne data. A survey showed that the dominant barrier, which blocks wide application of precision agriculture by farmers is cost (Robert, 2002). Meantime, the high altitude of conventional platforms makes it difficult to obtain high spatial resolution images (2 inches or less). The occurrence of UAV systems greatly changed the working mode of conventional systems and exhibited the great possibility to provide researcher and crop producers a steady, low-cost aerial platform for remote sensing.

UAV technology is mainly used by the military (>80 %) (UAS, 2007), but the civilian application began to take a considerable role in recent years although operators must comply Federal Aviation Administration (FAA) regulations to operate UAVs in the National Airspace (NAS). The wide application of UAV in agriculture came from three basic considerations: cost, resolution and convenience. Sensors on unmanned aerial vehicles (UAVs) could provide low-cost, high-resolution aerial images resolving major deficiencies of current image acquisition systems (Berni, J.et al., 2009) since UAVs can fly at a low altitude, close to the object of interest at different positions. Today, even with low cost GPS systems, UAVs can be navigated with decimeter accuracy and the orientation parameters can be used for navigation (Eisenbeiss, 2004). Other features such as vertical take-off (Jame, 1994), way points set in advance, easy to repeat flights make it attractive and practical. It is suggested that UAVs are going to make a great contribution to regional agricultural resource monitoring (S.R Herwitz et al, 2004). In the recent years, many researches have demonstrated that UAVs are a promising technology in agriculture applications (Xiang, 2011; Saari, 2011; Mäkynen, 2012; Garcia-Ruiz, Sankaran et al. 2013).

In this paper, we will explore the possibility to adopt a UAV system for tree and nursery inventory management. Once it is successful, farmers will be capable of monitoring their fields as needed. Image stitching technology and the flexibility of mounting a multitude of light-weighted sensors (e.g. digital camera, video recorder) on UAV systems could potentially monitor large crop production areas in real time.

MATERIAL AND METHODS

Nursery inventory management with uniform canopies

Preliminary test-ground based boom truck for green nursery crops management

An articulated boom (Hertz, USA) was used to deploy sensors from 9.14 m to 24.38 m (30 to 80 ft.) (Fig. 1). Sensors were mounted to an aluminum pole that extended 2m horizontally beyond the bucket. Images were taken after a proper location was obtained by adjusting the extendable boom. A plumb line was used to locate the center of the plant region to guarantee that the image had complete coverage of all the plants.

The digital camera used is a Canon EOS 5D Mark II. It is a 21.1-megapixel (5,616 × 3,744 pixels) full-frame, CMOS, digital, single-lens reflex camera.

Fig. 1. Articulated boom.

The experiment was conducted on 13 and 14 November, 2012 at the Citrus Research and Education Center (University of Florida, Lake Alfred, FL, USA). Region of interest (ROI) was a block of 100 containerized perennial peanut (Arachis glabrata) spaced in a 10 x 10 grid. The perennial peanut is fast growing crop with a uniform canopy resulting in a regular outline. The black polyethylene containers used were blow molded C200 pots with the following specifications: volume, 2.03 L; top diameter, 15.24 cm, height, 15.24 cm. Considering the altitude range of the articulated boom and the spatial resolution of the images, images were taken at the altitudes of 9.14, 12.19, 15.24 and 18.28 m (30, 40, 50, and 60 ft.). The container spacing was set as 0, 2.54, 7.62, 12.70, 18.28 and 22.86 cm (0, 1, 3, 5, 7 and 9 in.), respectively. In total, there were 24 (4 × 6) different combined conditions. For each condition, four replicates were taken. In order to validate the results, 20 plants were switched with 20 other plants inside the block randomly after photographing each replicate. The center plant was marked. Before each photo was taken, the operator on the boom would use a plumb line to check whether the camera was directly over the center point of a block in order to make sure the image did not deviate from the ROI. Although this was done, some images still deviated. The deviation reduced the available number of combined conditions to 17.

UAV system for commercial nursery field inventory management

An unmanned aerial vehicle (UAV) system was used at altitudes up to 4 km. The vehicle was powered by a 6600 mA h lithium ion polymer battery which can provide 10 to 20 minutes of flight time, depending on payload. It is capable of remaining stable under wind speeds up to 50 km/h (Garcia-Ruiz et al., 2013) preventing issues related to vibration causing image distortion. Waypoints can be established before or during the flight. A control board was used to trigger the sensor aboard the UAV system.

Two videos were recorded on May 23, 2013 and August 23, 2013 in ground field nursery (Cherry Lake Tree Farm, Groveland, Florida) in which crops were arranged in a rectangle. The UAV flew at a steady altitude of 31 meters from one end to another end (about 50m). The video recorder used was a Sony NEX-5n (Sony Corporation of America IR, San Diego, CA) with an 18-55 mm lens. It is autofocused and MPEG-4 1,440 x 1,080 was recorded at 30p on NTSC models. To guarantee a high overlap of the consecutive frames, the UAV system was flying at the speed of 3m/s. An image composite editor (ICE, Microsoft, Inc., Seattle, USA) was used to create the panorama image of the nursery field.

UAV system for yellow foliage nursery crops with fabric and gravel background (Experiment of University of Arkansas)

Container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) were spaced in staggered rows to achieve three canopy separation treatments: 5 cm between canopy edges (5 cm), canopy edges touching (0 cm), and 5 cm of canopy edge overlap (-5 cm). For each canopy separation treatment, a set of 64 containers (8 × 8) was established outdoors on a black polypropylene ground cover (Lumite, Inc., Alto, GA) on 14 July, 2013 and on gravel on 13 July, 2013. Treatment sets were replicated three times in a randomized complete block design (RCBD) for a total of 9 sets of plants. Set number 10 only had 56 plants. Four fully separated plants were positioned outside the east edge of the nine sets and were used to train the MATLAB algorithm. Shoot height was measured from the substrate surface to the top of the plant.

A Sony NEX-5n 16.1 megapixels color digital frame camera, with an 18-55 mm lens was used as the sensor. The shooting mode was set for intelligent auto resulting in images with an ISO of 200-250, shutter speed of 1/200-1/500, f value of 1/7.1-1/8. Autofocusing and aspect ratio of 3:2 were fixed.

Matlab Algorithm

A counting algorithm was written in Matlab (R2013b) based on the assumption that canopy area of container-grown plant varies little within block. The basic idea is to train the algorithm based on a small number of container-grown plants in order to obtain the canopy area of an individual. Once the area of an individual is known, then propagate that area information to large plant blocks to estimate the number of container-grown plants.

For image processing in Matlab, we mainly rely on the color and texture information to extract and analyze the plants. Color information we adopted to extract plants (e.g. yellow plants, green plants) from different background (fabric, gravel) is different. Main steps of the algorithm are discussed in the following.

Step 1-Extract the training plants: In our experiment, we placed 4 individual plants outside region of interest (ROI). The 4 plants are separately placed and have no overlap with adjacent plants. The first step is to choose the appropriate index to extract training plants from background. For green plants, since the green component is higher than that of blue and yellow. The value of excess green index (2G-B-R) of nursery plants will be larger than that of the background. We took advantage of this difference to extract green plant information from background. A global threshold was determined to binarize the image. To find a better threshold, image enhancement was implemented to improve the image contrast. White pixels on result image represent plants, while black pixels represent background.

For yellow plants, the difference of (Red-Green) is smaller than that of the background. A normalized index (Red-Green)/(Red+Green) is used to extract the plants and binarize the image.

In practical nursery filed, the spacing of the adjacent crops is significantly small and they are squeezed together with severe overlaps. If individual plants are taken as training plants. The area cannot represent the true canopy area. Hence we randomly chose the training sets from the real fields instead of the individual plant training set. Since the commercial nursery fields have green crops, we also took index (2G-B-R) to extract the training set.

Step 2-Post-processing and estimate the canopy area: The canopy area is defined as total pixels of one plant in the image. The second step is to estimate average canopy area based on 4 individual plants. Before we do the estimation, post-processing technology was applied to the result image in step 1 to fill the holes inside the plants and remove dots outside the plants that are falsely identified as plants. Morphology operation (erosion followed by dilation) is taken to deal with this issue. For green plants (in the boom truck system and practical field), since index 2G-R-B is capable to distinguish the plants from the background, we don't have many falsely identified pixels. After applying morphology (erosion followed by dilation) technology, we could generate an outcome image shown in Fig. 2a. For yellow plants with fabric background, there does not exist many falsely identified pixels outside the plants, morphology operation could produce a satisfactory result, similar to Fig. 2a. However, for yellow plants with gravel background, there are large yellow elements in the gravel background. When we extracted yellow plants from background, these elements would also be extracted (Fig. 2b). Erosion cannot eliminate the falsely identified pixels completely (Fig. 2c). We took an area threshold which is set based on the altitude of the images to be taken. If the area of the white region is smaller than the threshold, the region is removed. Otherwise, it is kept as the plant canopy. Average plant canopy (A) is calculated based on remaining white regions.

Step 3-Extract container-grown plants (ROI) from large block: Since we already got the reference canopy area (A) in step 2. The purpose of step 3 is to obtain the canopy area of region of interest. Green crops in preliminary experiment and commercial field are in a uniform, dark background. Excess green index (2G-B-R) was used to extract region of interest from large blocks to be counted.

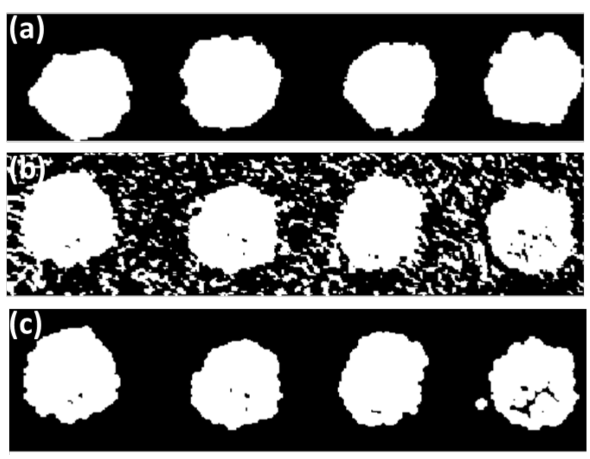

Fig. 2. (a) Green training plants and yellow training plants with fabric. (b) Yellow training plants with gravel background. (c) Result of applying morphology to (b) (The smallest region will be removed by area thresholding).

We have two different backgrounds (fabric and gravel) for yellow plants. In the case of fabric background, normalized index (Red–Green)/(Red+Green) works well to extract plants in large block since we have a uniform black cover. However, for gravel background, a lot of pixels were false identifies as plants. If these pixels lie outside of the large block, we can eliminate them based on 1) morphology technology (discrete pixels or small regions) or 2) thresholding on average plant canopy (relatively larger regions but smaller than canopy region). If these pixels lies between the plants in the large block, the may result in connection two adjacent plants and create an even larger white area which is the sum of two or more container-grown plants (Fig. 3a). This cannot be solved by the two methods mentioned above. Here, we created an index Dark=3-(Red+Green+Blue)-30*(Abs(Red-Green)) to extract the dark area between adjacent plants. If the pixel is darker, the index is larger. We can create a dark pixel map (Fig. 3b) according to this index. Finally, apply the dark map to the binarized image created by index (Red-Green)/(Red+Green). This would help to remove the false identified pixels among adjacent plants. The result image modified by the dark map is shown in Fig. 3c. For comparison purpose, the original color image is shown in Fig. 3d.

Step 4-Propagate the canopy area (A) in the training set to plants extracted in large block then estimate the number of plants (interval counting): With the information from step 2 and step 3, our goal here is to provide a relationship between A and canopy area of region of interest. Since we assume that the plants bear a uniform canopy. We came up a scheme called interval counting to estimate the count number based on A.

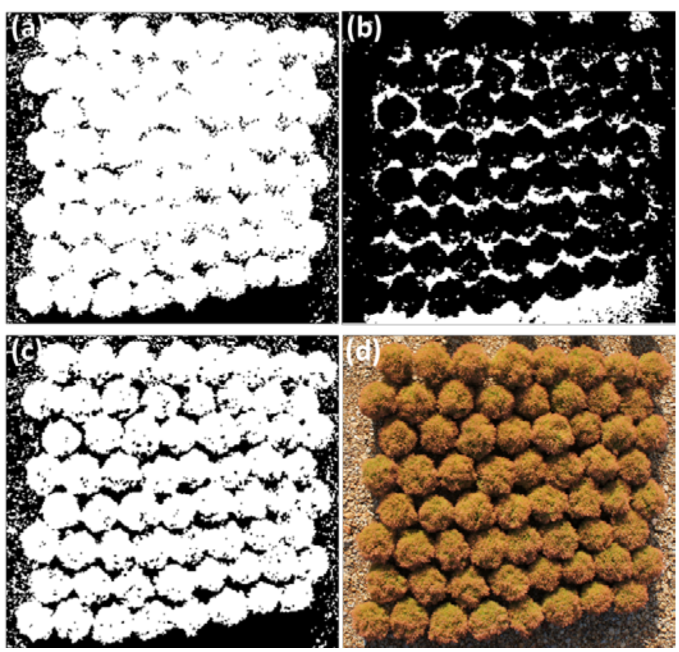

Fig. 3. (a) False pixels connect adjacent plants. (b) Dark map. (c) Result image after modification. (d) Original color image.

Fig. 4. (a) Flowchart of the process (b) Intensity distribution of (G-R) grayscale image.

Take A as a basis, if the area of white region is smaller than 0.5×A, then it is counted as 0. If the area lies in the range of 0.5×A and 1.0×A, it is counted as 1 plant. Continue the process until all the white regions are included. Sum up the counted plants together which is the total count.

Christmas tree inventory management without uniform canopies

Coniferous trees such as Christmas trees are most easily identified by the cone shape. This spatial structure varies the reflectance results in a local maximum value at or near the center of trees. In this section, an image-processing algorithm was developed based on this special character in Christmas tree to identify the individual trees and count them in an aerial image. For coniferous trees, local maximum filtering will be used. A window with fixed size will pass over all the pixels and check if a given pixel is with higher reflectance than other pixels within the window. Pixels with largest digital number in the window will be marked as a tree location. The flowchart of the processing is shown in Fig. 4a.

Matlab Algorithm

Step1-Pre-processing: In order to extract the region of interest and remove background, grayscale image of component (G-R) was extracted. Moreover, a Gaussian filter was used to remove the noise and smooth image. Fig. 4b shows the intensity distribution of the processed image.

Step 2-Local maximum filter: A window with fixed size (25 pixels*25 pixels) will pass over all the pixels and check if a given pixel is with higher reflectance than other pixels within the window. Pixels with largest digital number in the window will be marked as a tree location. Tree locations after local maximum filter are shown in Fig. 5a.

Step 3-Minimum distance filter (MDF): After the local maximum filter step, we found that one tree was detected many times. This will result in a high commission error. To reduce the commission error, a minimum distance filter was used. The principle of MDF is that if the distance of two points identified as tree locations lies inside a threshold (we pre-set that threshold to 30), then one point will be removed. Fig. 5b shows the outcome image after MDF.

Step 4-Remove false identified tree in background: In Fig. 5b, some locations in the background are falsely identified as tree. Here, based on the histogram difference of the tree, soil and grass, the false locations in the background are removed. Fig. 6 compares histograms of R、G、B、H、S、V components of trees and background (green represents trees, blue represents background). S component of trees and background are fully separated here. If S value of the identified location is smaller than 60, it will be removed. Otherwise, it is pertained. Fig. 5c shows the outcome image after false tree locations removed.

RESULTS AND DISCUSSION

In this section, we discussed the results consistent with experiments described in M&M section.

Nursery inventory management with uniform canopies

Preliminary test-Ground based boom truck for green nursery crops management

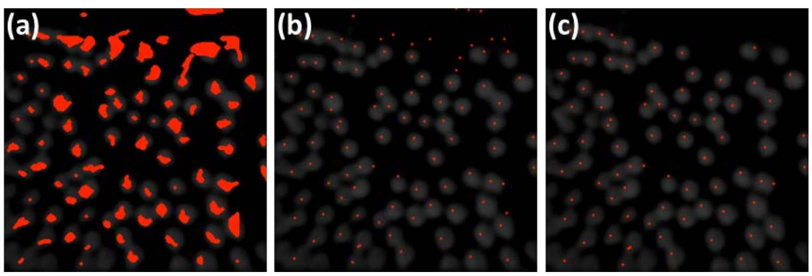

Fig. 5. (a) Tree locations identified by local maximum filter. (b) Tree locations identified after minimum distance filter. (c) Outcome image after false tree locations removed.

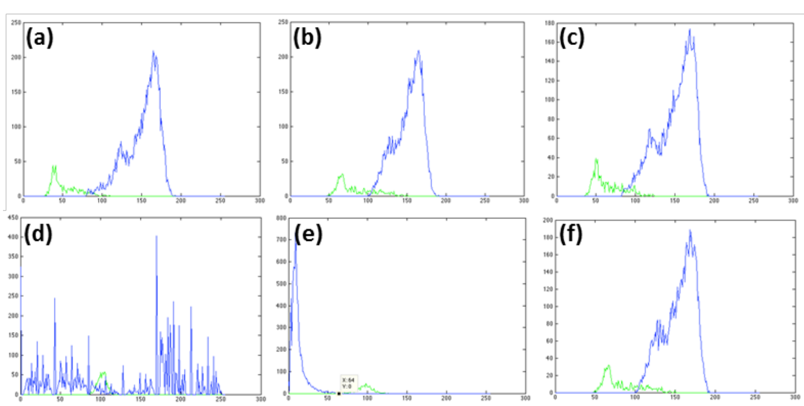

Fig. 6. (a-f) Histograms comparison of R, G, B, H, S, V components.

Table 1. Preliminary counting results using a boom truck

Height (feet)	Space (inch)	Disk size	Rep1 count	Rep2 count	Rep3 count	Rep4 count	Average count	Actual count	**Error**
30	0	3	115.0	114.0	119.0	------	116.0	117.0	**-0.9%**
	1	3	104.0	102.0	104.0	107.0	104.3	104.0	**0.2%**
	3	3	102.0	102.0	101.0	102.0	101.8	104.0	**-2.9%**
	5	3	112.0	113.0	116.0	117.0	114.5	104.0	**10.0%**
	7	3	102.0	100.0	101.0	99.0	100.5	100.0	**0.5%**
	9	3	100.0	99.0	101.0	100.0	100.0	100.0	**0.0%**
40	1	3	105.0	104.0	105.0	105.0	104.8	104.0	**0.7%**
	3	3	105.0	105.0	105.0	105.0	105.0	104.0	**1.0%**
	5	2	104.0	103.0	102.0	103.0	103.0	104.0	**1.0%**
	7	2	105.0	106.0	106.0	105.0	105.5	104.0	**0.5%**
	9	2	100.0	101.0	100.0	102.0	100.8	100.0	**0.8%**
50	5	2	99.0	97.0	98.0	99.0	98.3	100.0	**-1.8%**
	7	2	105.0	105.0	105.0	105.0	105.0	104.0	**1.0%**
	9	2	105.0	107.0	106.0	106.0	106.0	104.0	**1.9%**
60	5	2	70.0	69.0	69.0	69.0	69.3	70.0	**-1.1%**
	7	2	105.0	106.0	106.0	107.0	106.0	104.0	**1.9%**
	9	2	105.0	106.0	106.0	106.0	106.0	104.0	**1.9%**

Table 1 shows counting results for green foliage nursery crops growing on black ground fabric. Images were taken from boom truck. An ANOVA test showed that the observed counting and the actual counting were not significantly different (α=0.05).

UAV system for commercial nursery field inventory management

We had more success with stitching from video than static images. The aerial picture (Fig. 7a) was created from video file recorded on May 23, 2013. At the last block (row 34-47), UAV system was preparing to land. Hence, the flying altitude was lower than that of all the previous blocks. Workers counted the nursery crops manually and we treated that number as the ground truth that was compared to the results from the software. The two crops in the yellow rectangle were randomly chosen as training set. The counting result of each block is shown in Table 2.

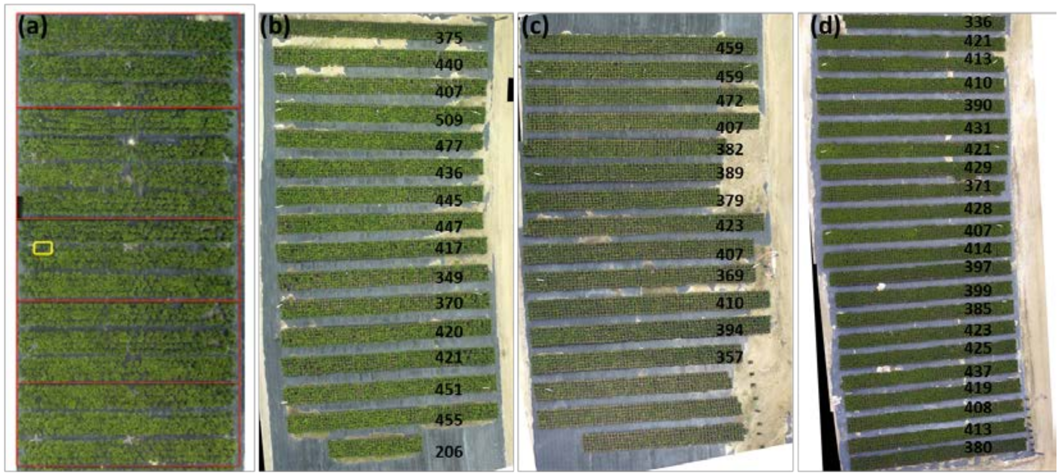

Fig. 7. Panorama image created by ICE.

Table 2. Counting results of the nursery field recorded in May

Row #	Algorithm Count	Manual Count
99-114	495	499
79-97	514	553
64-77	464	425
49-62	429	422
34-47	489	418

From Table 2, we can easily conclude that the counting error of the last block was much higher than other blocks. This is because the altitude of aerial platforms was lower when the video was recording at the last block. Hence, the number of pixels which one nursery crop covers increased. In other words, the canopy area of this block was larger than that of other blocks. Hence, if we applied the training area calculated by previous blocks, the counting number of the last block will be overestimated. This is consistent with what we have observed.

The count results from the video file recorded on August, 2013 is shown in Fig. 7b-7d. The count on the side was calculated from our image processing software. There were about 22,000 plants in that block (three pictures). The only issue that we had was with three blocks in Fig. 7c. For some unknown reason, the plant look different (more yellow) and because of that our algorithm didn't work well. If these three blocks are included, our count came very close to 22,000 (within five percent). This is a realistic case with overlap plant canopy yet the algorithm worked reasonably well. It is even hard for human to count these pots

UAV system for yellow foliage nursery crops with fabric and gravel background (Experiment of University of Arkansas)

Table 3 shows the counting accuracy of yellow nursery crops on fabric ground cover.

Table 3. Total count errors for container-grown Fire Chief ^{TM} arborvitae (Thuja occidentalis L.) on a black fabric ground cover using MATLAB.

Canopy Separation(cm)	Counting Accuracy
5	6%
0	-5%
-5	-28%

A high counting error was occurred when the canopy separation is -5cm. This is because for set 3, set 7 and set 9 at each height, the plants in the block are severely squeezed. Hence, it is impossible to take the average area of the 4 individual training plants to represent the area of the plants in the 6*6 block. The counting results will be greatly underestimated.

Here, we exacted the counting results of set 3, set 7 and set 9 and compared with ground truth counting. We found out the squeeze ratio (ground counting/algorithm counting) is close to a constant in each set, respectively. Knowing that, we took that ratio to correct the average area of the 4 training plants, the corrected training area is calculated by (average area of 4 plants/ squeeze ratio). Table 4 shows the average correction ratio for each severely overlapped set.

The squeeze ratio was applied to the counting with gravel background. Counting accuracy for yellow container plants on gravel is showed in Table 5 after correction.

Table 4. Correction ration for different set.

Set number	Correction Ratio
3	1.34
7	1.27
9	1.56

Table 5. Count errors for container-grown Fire Chief TM arborvitae (Thuja occidentalis L.) on gravel as ground cover using MATLAB®

Canopy separation (cm)	Flight altitude (m)					
	6		12		22	
	Count error	%	Count error	%	Count error	%
5	1	2%	2	3%	3	5%
0	-2	-3%	-5	-8%	0	0%
-5	2	3%	0	0%	2	3%

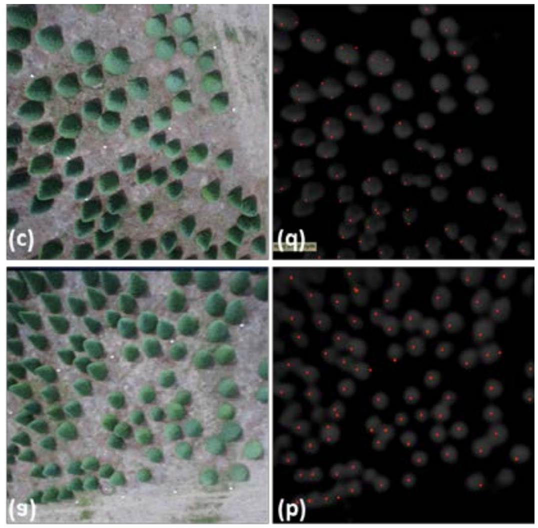

Fig. 8. Results for Christmas tree count with non-uniform canopy. (a) Actual Counting=86. (b) Algorithm counting=83. (c) Actual Counting=74. (d) Algorithm counting=76.

Clearly, after applying the correction factor for plants with canopy separation -5cm, the counting accuracy improved. This proves again that the training area should be consistent with area which is covered by the canopy from the image view.

Christmas tree inventory management without uniform canopies

We displayed the original image with manual counting results and outcome image with algorithm counting results in Fig. 8. We don't have many testing image available. The red dot in the outcome image represents each tree detected by the algorithm.

In test image 2, we can notice a high commission error. This is because we apply a MDF to decrease the commission error. If we set the threshold too large, two close trees will be identified as one tree. This will increase the omission error. However, if the threshold is too small, one single tree with large canopy area will be identified as two or more trees like image 2. The value of the threshold of MDF is a trade-off between commission and omission error.

CONCLUSIONS

Two counting algorithm targeting at uniform canopy nursery and non-uniform canopy nursery were developed in this paper. We applied uniform counting algorithm to aerial images of experimental nursery field with boom truck and UAV system. Results were compared with different shooting heights and canopy separation distance. Also, algorithm was tested on aerial images of practical nursery field stitched from a video. In both case, counting accuracy lies inside 10%. This indicates that the algorithm works well with high shooting altitude (up to 60m), canopy overlapped (with -5cm separation) and low-resolution image (created from video). Non-uniform counting algorithm was applied to Christmas tree counting. Although we don't have many test images, the two test cases showed that the counting accuracy lies inside 5%.

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