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Use of Remote Imagery and Object-based Image Methods to Count Plants in an Open-field Container Nursery

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By

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ABSTRACT

In general, the nursery industry lacks an automated inventory control system. Object-based image analysis (OBIA) software and aerial images could be used to count plants in nurseries. The objectives of this research were: 1) to evaluate the effect of an unmanned aerial vehicle (UAV) flight altitude and plant canopy separation of container-grown plants on count accuracy using aerial images and 2) to evaluate the effect of plant canopy shape, presence of flowers, and plant status (living and dead) on counting accuracy of container-grown plants using remote sensing images. Images were analyzed using Feature Analyst® (FA) and an algorithm trained using MATLAB®. Total count error, false positives and unidentified plants were recorded from output images using FA; only total count error was reported for the MATLAB algorithm. For objective 1, images were taken at 6, 12 and 22 m above the ground using a UAV. Plants were placed on black fabric and gravel, and spaced as follows: 5 cm between canopy edges, canopy edges touching, and 5 cm of canopy edge overlap. In general, when both methods were considered, total count error was smaller [ranging from -5 (undercount) to 4 (over count)] when plants were fully separated with the exception of images taken at 22 m. FA showed a smaller total count error (-2) than MATLAB (-5) when plants were placed on black fabric than those placed on gravel. For objective 2, the plan was to continue using the UAV, however, due to the unexpected disruption of the GPS-based navigation by heightened solar flare activity in 2013, a boom lift that could provide images on a more reliable basis was used. When images obtained using a boom lift were analyzed using FA there was no difference between variables measured when an algorithm trained with an image displaying regular or irregular plant canopy shape was applied to images displaying both plant canopy shapes even though the canopy shape of 'Sea

Green' juniper is less compact than 'Plumosa Compacta'. There was a significant difference in all variables measured between images of flowering and non-flowering plants, when non-flowering 'samples' were used to train the counting algorithm and analyzed with FA. No dead plants were counted as living and vice versa, when data were analyzed using FA. When the algorithm trained in MATLAB was applied, there was no significant difference in total count errors when plant canopy shape and presence of flowers were evaluated. Based on the combined results from these separate experiments, FA and MATLAB algorithms appear to be fairly robust when used to count container-grown plants from images taken at the heights specified.

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INTRODUCTION

This study named “Use of Remote Imagery and Object-based Image Methods to Count Plants in an Open-field Container Nursery”, explores factors involved in the potential use of aerial images as a method to count plants in open-field nurseries. One factor evaluated was flight altitude of an unmanned aerial vehicle because flight altitude affects image spatial resolution and therefore, data quality. Plant canopy separation, plant canopy shape, presence of flowers and plant status (living or dead) were also evaluated. These factors were given priority after achieving competency with object-based methods based on an understanding of critical factors at this time. Two different object-based image methods were used to analyze the images collected.

CHAPTER ONE: LITERATURE REVIEW

Plant inventory in nurseries

Despite the dramatic growth in the U.S. Green industry from 1988 to 2008, management and production practices have not been well documented (Hodges et al., 2008; Schuch and Klein, 1996). In general, the nursery industry lacks a good inventory control system (Harkess, 2005). Nursery growers collect plant inventory for tax purposes, order management and estimation of crop yield. Plant inventory data can be comprised of plant count and/or plant grade information (e.g. canopy width and height, canopy uniformity). Inventory management is an integral and essential practice in every business pursuing the maximization of its value (Michalski, 2009). The process of collecting inventory data is labor intensive involving the physical counting of thousands of plants in a nursery (Harkess, 2005). The process is further complicated when plants are removed from production due to mortality and shipping (Hale, 1985; Rafter, 2006; Vanik, 2012). Once inventory data are collected it must be entered into a database (Rafter, 2006). Some forest tree nurseries have based inventory on systematic plot sampling with some adjustments according to past experience, species, densities, typical grading and cull rates (Hale, 1985). At Greenleaf Nursery, Park Hill, OK, plant counts are collected manually once a production block is filled by one employee and recorded on paper logs (M. Andrew, personal communication, 14 June 2014). These logs are transported from the field to the office where the data are entered into a database manually. As plants increase in width, containers are spaced and the block is re-counted. Many times this ‘spread count’ is conducted just prior to a grade evaluation (i.e. growth status, saleability, quality) by the inventory manager. These counts are very important because sales bookings from customers come in during fall and order acknowledgements are generated based upon counts of crop availability. Most blocks are re-evaluated and re-counted again during the winter to make sure the inventory is as accurate as possible prior to spring shipping. Reporting accuracy for this nursery is estimated at 95-100% but likely decreases for crops with large numbers or specific production issues (e.g. pest or environmental problems).

One improvement in collecting inventory data was the implementation of barcodes and Radio-Frequency Identification (RFID). Using bar-code scanning devices and Counterpoint® Software (Radian Systems Inc, Alpharetta, Georgia), Tri City Nursery in Utah, which grows trees and shrubs, decreased the size of the inventory crew from eight to ten persons to one or two, and decreased the time required from one month to two weeks (Janam Technologies, 2011). However, this technology proved to be problematic due to foliage growing over the barcode or water and dust covering it which causes errors when trays are being scanned on a production conveyor belt (Swedberg, 2009). Nevertheless, this system may not be suitable in large container nurseries which, in states like California, constituted more than 80% of nursery producers (Schuch and Klein, 1996). RFID has been used to track and count trays of seedlings in seedling production greenhouses. Also, plant damage has been reported when using tags inserted inside trunks (Luvisi et al., 2010). Although RFID is being investigated for use in nurseries, it has not been adopted commercially (Saraswat and Robbins, 2011).

One advancement in the inventory process is the development of software/hardware to transmit manual inventory counts from the field to inventory databases (Brownsberger et al., 2001; Vanik, 2012). Several software programs have been developed to address plant sales inventory and track data in nurseries for different sized operations. Tracking data includes vendor and region, propagation source, growing locations and conditions, insurance value, container size, plant age and grade (Anonymous, 2007; McClellan, 2012; USDA, 2013; Willamete PC Service, 2013). Some software examples include: Arc Growing Software®

(Innovative Software Solutions, Grand Rapids, MI), Desktop Inventory Control® (Small Business Innovations Inc., Portland, OR), Handheld Inventory Control® (Small Business Innovations Inc., Portland, OR), Production Management® (Small Business Innovations Inc., Portland, OR), Retail Pro® (Canadian Retail Solutions, Alberta, Canada) and AMS Point of Sale® (AMS Retail Solutions, Virginia Beach, VA). In general, a limitation of these software programs is that they still require the manual collection of inventory data. Different efforts have been evaluated to improve plant inventory practices.

Devoe and Kranzler (1985) analyzed images to obtain inventory for tree seedlings. This method demonstrated the potential to improve field estimates of pine tree seedlings with an average error of 4%. Use of an unmanned aerial vehicle (UAV) may be one method to obtain plant inventory data for nurseries and Christmas tree farms in the future. A UAV was used to count the number of citrus trees in a Florida grove with accuracies as high as 94% (Anonymous, 2011). Remote sensing applications are discussed in greater details in subsequent sections.

An informal survey about plant inventory practices in nurseries was conducted in August 2011 at an American Nursery and Landscape Association Management seminar (J. Robbins, personal communication, 23 August, 2011). Based on gross sales, growers expressed that on average 53% of their nursery plants are gown in containers and 47% in the field. Twenty nine percent of the growers indicated that a minimum of 10% of their annual gross sales are lost because plant count was inaccurate or was not made at the correct time. More than a half of field growers (55%) collect inventory counts two times per year, while 64% of container growers collect inventory counts three or more times per year. On average, survey respondents indicated they spend $61,000 (2.8% of gross sales) conducting plant counts. Although grower’s responses were not verified (self-reported), 33.7% of the growers stated that count accuracies were lower than 90%. Willow Nursery, Ehphrata, WA, spends about $30,240 per season on labor for counting tree fruit rootstock grown on 300 acres. The time required to perform this task is about three weeks for 15 workers (S. Sankaran, personal communication, 19 June, 2014). The type of inventory system required will depend on the size of the nursery. Large, complex nurseries would require a rather complex system, while the inventory system for small operations may be quite simple (Anonymous, 2007). Automating the plant inventory process may potentially decrease labor inputs and increase accuracy.

Applications of remote sensing/aerial images in agriculture

Improvements in digital imagery resolution and spectral and spatial resolution of remote sensors have made it possible to produce high quality data for environmental and agricultural applications. Remote sensing techniques enable the generation of specific technical parameters that can be used as required by different fields of study (Wulder et al., 2000).

Several researchers have investigated the use of aerial images for agricultural applications. Some of these applications include: measurement of water stress (Lebourgeois et al., 2012), evaluation of nitrogen concentration (Hunt et al., 2005; Lebourgeois et al., 2012), plant disease identification (Ayyalasomayajula et al., 2009; Garcia-Ruiz et al., 2013), and land use/land cover classification (Riggan and Weih, 2009; Ruiz et al., 2011). Remote sensing imagery has been used for tree crown identification and tree species classification (Wulder, 1998; Wulder et al., 2000; Pitkänen, 2001; Haara and Haarala, 2002; Carleer and Wolff, 2004; Hájek, 2006), and to measure forest health (Haara and Nevalainen, 2002).

Pixel- and object-based image analyses are the most common approaches for automated feature classification with different levels of complexity. Object-based image analysis (OBIA) includes more variables in the process that increase accuracy of the classification when using high spatial resolution imagery (Riggan and Weih, 2009). In Spain, a software application for object-based image analysis was developed to characterize and classify agricultural land cover (Ruiz et al., 2011). Feature extraction algorithms were used to develop a dynamic environment. Textures, spectral data, normal digitized index vegetation (NDVI) values and feature shapes attributes were integrated as inputs in the software. An overall classification accuracy of 65.5% was achieved when linear discriminant analysis (LDA) was used. Using digital images and pixel-based classification, Bumgarner et al. (2012) conducted real time non-destructive assessment to correlate leaf area index with destructive methods from green and red leaf lettuce. Experiments were conducted in outdoor, high tunnel and greenhouse settings. WinCAM® software (Regent Instruments, Quebec, QC, Canada) was used for image analysis. Significant correlations of 0.85 to 0.96 were observed 7 to 16 days after sowing under greenhouse conditions when canopy cover data from both methods were compared. Alternatively, under outdoor and high tunnel conditions, correlations were 0.71 to 0.95, 16 to 30 days after sowing. A limitation of this study was the use of a fixed platform which would limit its commercial use. This classification process is color based, and the canopy cover calculated from the images appears to be based on all the plants and not on individual plants, which may be practical for this application but not for open-field nursery inventory.

Shrestha and Steward (2003) measured early growth stages of corn development, V3 to V4, using a machine vision-based corn plant population sensing system. Video was obtained from a mobile ground vehicle at 0.60 m above the ground, and then algorithms were developed to count corn plants. Results were compared with manual stand counts. When weed population was low, a high correlation with manual counts was reported (r^2=0.90). Variability in plant size and leaf orientation was cited as the most important sources of error. As in many businesses, nurseries aim to produce a uniform product: plants that are similar in shape, size, and color, however, variations in plant characteristics should be considered when using remote sensing data. In order to adequately evaluate the variability in a typical nursery production block, treatment blocks should be large enough to mimic the dynamics of a production setting.

Features identification: Tree crown identification under forest conditions

Identification of tree diversity and dispersion is a practice used to manage and conserve forest bio-resources (Parthasarathy and Karthikeyan, 1997). Biodiversity as a result of human activities has led to the development of powerful and affordable methods to quantify species diversity (Chiarucci and Palmer, 2006). Conventional forest tree inventory methods have been based on tree sampling that does not require extra equipment and involves familiar techniques to many practitioners (Ducey et al., 2002). Tree identification and counting is a common application of remote sensing data. Identification of individual plants within aerial imagery is the main challenge to get an accurate count. Image quality, stand physiognomy, and photo-interpreter skills are the main factors that influence crown counting accuracy (Karantzalos and Argialas, 2004). Tree crown delineation in forest settings has been achieved using different methods and input data with accuracies ranging from 48% to 92% (-52 to -8% count error) (Pouliot et al., 2002; Leckie et al., 2003; Bunting and Lucas, 2006).

Carleer and Wolff (2004) used high spatial resolution satellite images to identify tree species from a forest. Image resolution was 4 m in the multispectral bands and 1 m in the panchromatic band. Image analyses achieved an overall accuracy of 79% for non-filtered images and 86% when filtered. Omission errors were due to the similarity in spectral signatures of the classes, resulting in incorrect classifications. Using aerial images taken with 50 cm spatial resolution, Pitkänen (2001) identified individual trees by combining binarization and local maxima procedures. Overall accuracies varied from 50 to 96%. The binarization method caused large variation between the features classified. Stand density was inversely correlated to the percentage of detected trees. The challenge in detecting individual trees in aerial images was to separate tree crowns from the background and from each other. The overall accuracy when images were analyzed with no binarization in comparison to binarization methods was small; however the absence of statistical analysis limits the interpretation of the results. Shank (2009) concluded that Feature Analyst® (FA) software has the potential to extract trees from aerial images when individual trees and shrubs were sufficiently separated from each other at a spatial resolution of 2.4 m; trees proximal to other trees, trees forming conglomerates, and trees underneath larger trees were stated as sources of error.

Haara and Nevalainen (2002) detected dead or defoliated spruce trees using infrared aerial images with a spatial resolution of 25 cm. One image was taken with the stand illuminated at the front, a second image at the nadir point. Trees were segmented and classified into six classes: pines, spruces without defoliation or slightly defoliated, spruces with moderate defoliation, spruces with severe defoliation, deciduous trees and dead or dying trees. Normalized Difference Vegetation Index (NDVI) and supervised learning were used in the final classification. Analyses utilizing band indexes resulted in greater detection of pines and spruces than when differences in band intensities were used. Overall accuracy was 60.1% when the stand was illuminated from the front and 84.3% when illuminated from the nadir point. Reliability of the training data were also considered as an important source of error. Selection of training sets is difficult due to the large variations of the features within images. With the goal of using semi-automatic delineation of individual tree crowns for identifying tree species, Haara and Haarala (2002) found higher classification accuracies when using training sets from the same images. When training sets were located at the nadir point, accuracy decreased due to the difference of the view angle. Higher accuracies were reported when light conditions were similar. When light conditions are variable in images, training sets must be increased in number. These results suggest that selection of training sets needs to represent the variations in light and view angle conditions within images to be analyzed.

Identification of forest tree species composition using eCognition (Definiens Imaging GmbH, Germany) was assessed by Hájek (2006) using satellite images with a 4 m spatial resolution and near infrared bands. Overall classification accuracy for *Picea* and *Larix* conifer species was over 90% due to their differences in spectral signatures. *Fagus* trees were classified with a lower accuracy (70%). *Betula* was the most problematic tree class and often confused with *Larix*. These two tree species have similar spectral and textural characteristics especially at a young age and was stated as the main reason for omission errors. Brandtberg (2002) reported classification accuracies from 76 to 80% when classifying Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) Karst.), birch (*Betula pubescens* Ehrh.) and aspen (*Populus tremula* L.) using 10 cm spatial resolution images.

Tiede et al. (2005) developed an algorithm using laser scanning data to identify trees in aerial images from a forest. 51% of the trees were identified, however, higher accuracies (>92%) were achieved when tree height was more than ten meters. Accuracy dropped to 28% when forests were juvenile and dense. Wulder et al. (2000) reported that to achieve reliable identification accuracy, the minimum tree crown radius needed to be 1.5 m. Tree crown diameters were less than 1 m and greater than 4 m. Overall accuracy was 67%. They concluded that omission errors are largely a result of the coarse spatial resolution. Pitkänen (2001) found that a spatial resolution of 50 cm was a limiting factor for tree crown identification. However, Uuttera et al. (1998) stated that the requirements of spatial resolution for forestry applications are low, although specific values were not provided. Alternatively, Cushnie (1987) suggested that increasing spatial resolution could complicate land cover classification process due to an increase in spectral signature variability. The canopy width for nursery plants is typically smaller than for forest trees, suggesting the need for higher spatial resolution images. Combination of similarities between spectral signatures, spatial distribution of features, and imagery spatial resolution could complicate the classification process. Once the camera resolution is fixed, spatial resolution can be increased by lowering the altitude at which images are taken. Also, spectral signatures of the ground cover used at a nursery or color changes in the plant foliage for water stressed plants (which also affects spectral values) may influence the ability to differentiate plants from the background.

Unmanned Aerial Vehicles (UAV) applications in agriculture

Many types of aerial platforms have been used to take aerial images since the middle of the eighteen century including balloons, kites and aircraft (Shellito, 2012). Each type of aerial platform offers advantages and disadvantages (Hunt et al., 2005). Balloons and kites are difficult to direct and the orientation and altitude depends on wind speed. The use of kites to take images is limited by wind speed, restricting periods when data can be collected and altitudes at which pictures are taken (Aber et al., 2002); however, this platform is less expensive than UAVs and satellites. Satellite images can be used depending on the level of resolution required (Shellito, 2012), however, they are not available on an as-needed basis and resolution is low even when using multispectral bands. Small objects like young trees and small nursery plants are difficult to recognize from satellite images and atmospheric issues can decrease image quality (Carleer and Wolff, 2004). Although satellites have sensors that can record higher resolution imagery, the government limits their distribution and commercialization (Shellito, 2012). Manned airplanes can be used to obtain aerial images, however, disadvantages of the platform include limited spatial coverage and image quality, which is dependent upon weather and cost (Hunt et al., 2005: Morgan et al., 2010). UAVs offer several advantages when used on agricultural applications including: vertical take-off and landing, on demand capability, customizable resolution, implementation of a flight plan using GPS coordinates, and automatically gyro compensated system to maintain the camera parallel to the ground (Ehsani and Maja, 2011; Robbins et al., 2012). When counting plants aerial images need to be taken frequently due to frequent changes in the production fields (McCoy, 2005). Nursery growers do not count their plants as often as needed due to the time involved and the expense (S. Doane, personal communication, 8 May, 2008). In order to automate plant counting, access to timely images with medium to high resolution are required.

UAVs are increasingly being used in agricultural applications including disease identification (Techy et al., 2010; Aylor, et al., 2011; Garcia-Ruiz et al., 2013), crop monitoring (Thomson and Sullivan, 2006, Furfaro et al., 2007;), vegetation monitoring (Berni, et al., 2009), forestry characterization (Grenzdörffer et al., 2008; Dunford, et al., 2009) and weed monitoring (Ramezani Ghalenoei et al., 2009; Torres-Sánchez et al., 2013). High resolution imagery has proven useful to detect and diagnose Huanglongbing (HLB) infected citrus trees in Florida (Garcia-Ruiz et al., 2013). Multispectral images obtained from an aircraft (altitude: ~590 m above ground level, speed: 65 knots) and a UAV (altitude: 100 m above ground level) were compared. Stepwise regression analyses were implemented in order to extract features from the images. Four algorithms were developed to distinguish between healthy and HLB infected trees. Images from the UAV yielded accuracies between 67-85% (7-32% false negatives) while images from the aircraft were between 61-74% (28-45% false negatives).

Object-based methods

Since OBIA software can accommodate more attributes than pixel-based methods it is gaining in popularity (Blaschke, 2003). As a result, commercial OBIA software packages such as eCognition® and Feature Analyst® (Overwatch System Ltd. Austin, Texas) have been recently developed (Riggan and Weih, 2009). While eCognition is the most popular OBIA software used (Blaschke, 2003; Robson et al., 2006; Riggan and Weih, 2009) it is more difficult to learn.

Feature Analyst® (FA) is a software plug-in for Esri ArcGIS®, Overwatch's ELT/5500® and Global Image Viewer® software. FA permits geospatial analysis and feature extraction from images for such features as vegetation, roads, buildings, rivers and lakes (Visual Learning Systems, Inc, 2004; Riggan and Weih, 2009). FA has been used in land cover classification (Blundell et al., 2008; O'Brien, 2003) and impervious feature classification (Lavigne et al., 2006). Standard OBIA software involve a segmentation, segment-classification, and generalization as part of its work-flow (Tsai et al., 2011). On the other hand, FA use spectral and spatial attributes to classify single pixels according to target and background data. FA applies a proprietary machine learning algorithm modeled by human visual image interpretation. In general, FA functions by segmenting individual objects into vector boundaries using a 'sample' created by the user; data from the 'sample' (e.g. spectral values and spatial data) are then correlated with target objects (Blundell and Opitz, 2006).

Several factors contribute to the complexity of imagery used for plant inventory analysis including plant characteristics (plant color, species, plant size and shape, canopy cover, plant health), ground/surface characteristics (bare soil, gravel, ground cloth), and environmental factors (sunlight/shadows). Because these factors could modify the data obtained from remote sensing images, these conditions must be noted when using these images. The development of an automated plant counting tool for the nursery industry could decrease labor inputs, increase precision and save money. Therefore, the process must be faster and more accurate than current manual methods used. The count of plants could be done automatically using aerial images. The objective of this research was to evaluate the effect of flight altitude, canopy separation, ground color, flower presence, and plant status (i.e. living or dead) on the counting accuracy of container-grown plants using object-based methods.

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CHAPTER TWO: EFFECT OF FLIGHT ALTITUDE (SPATIAL RESOLUTION) AND CANOPY SEPARATION ON PLANT COUNTING ACCURACY USING BLACK FABRIC AND GRAVEL AS GROUND COVER

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Abstract

In general, the nursery industry lacks an automated plant counting system. Aerial images have proven useful in counting plants in forest, citrus grove and nursery settings. The recent development of object-based image analysis (OBIA) software permits geospatial analysis and processing from images for features such as vegetation, roads, buildings, rivers and lakes. The objective of this research was to evaluate the effect of flight altitude and plant canopy separation of container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on count accuracy. Images were taken at 6, 12 and 22 m above the ground using an unmanned aerial vehicle (UAV). Plants were placed on two ground covers, black fabric and gravel, and spaced in staggered rows to achieve three canopy separation treatments: 5 cm between canopy edges, canopy edges touching, and 5 cm of canopy edge overlap. Count algorithms were trained using Feature Analyst® (FA) and MATLAB®. Total count error, false positives and unidentified plants were recorded from

output images using FA; only total count error was reported for MATLAB. In general, when both methods were considered, total count error was smaller [ranging from -5 (undercount) to 4 (over count)] when plants were fully separated, with the exception of images taken at 22 m that yielded total count errors between -11 (undercount) and 5 (over count), regardless of canopy separation. FA showed a smaller total count error (-2) than MATLAB (-5) when plants were placed on black fabric. On the other hand, when plants were placed on gravel, MATLAB resulted in a smaller overall total count error (1) than FA (-8). When images were analyzed using FA, total count error (average over at all flight altitudes and canopy separation treatments) for plants placed on gravel (-8) was larger than for those on a black fabric (-2), however, false positive counts were similar for black fabric (6) and gravel (6) ground covers. Since false positive counts using FA were not different between ground covers, total count errors are more likely to be affected by unidentified plants, which was smaller for plants placed on black fabric (9) than those placed on gravel (14). Nevertheless, output images of plants placed on gravel did not show a negative effect due to the ground cover; higher total count errors might be caused by larger variation in image spatial resolution for plants placed on gravel. Based on these preliminary results, further research is required to improve counting results using different algorithms, sensors, and aerial platforms.

Keywords:

nursery, OBIA, UAV, MATLAB, Feature Analyst

Introduction

Despite the dramatic growth in the U.S. Green industry from 1988 to 2008, management and production practices have not been well documented (Hodges et al., 2008; Schuch and Klein, 1996); plant inventory control is part of these management practices. In general, the nursery industry lacks an automated inventory control system (Harkess, 2005). Counting plants in a nursery is a labor intensive process involving the physical counting of thousands plants. Due to the time involved in manually counting plants, forest and nursery tree growers often count only a portion of their crop (Hale, 1985; S. Doane, personal communication, 8 May, 2008). The process is further complicated when plants are removed from production due to mortality and shipping (Hale, 1985; Vanik, 2012).

In the last few years improvements have been made in the inventory process such as the adoption of software (Hodges et al., 2008; USDA, 2013) and mobile personal digital assistants (Brownsberger et al., 2001). While these technologies have helped in the processing of inventory data, data are still collected manually. Other technologies such as radio frequency identification (RFID) and bar codes are helping with the collection of inventory data; however, they have limitations such as the need for a line-of-sight, signal transmission errors (Janam Technologies, 2011; Saraswat and Robbins, 2011), plant damage (Luvisi et al., 2010) and adaptability into large nurseries (Schuch and Klein, 1996).

Improvements in digital imagery resolution and spectral and spatial resolution of remote sensors have made it possible to produce high quality data for environmental and agricultural applications. Aerial images have proven useful in counting plants in forest, citrus grove and nursery settings (Devoe and Kranzler, 1985; Wulder, 1998; Wulder et al., 2000; Pitkänen, 2001; Tiede et al., 2005; Ayyalasomayajula et al., 2009; Robbins et al., 2011). Several methods have been developed to accurately identify and count tree crowns in forest settings. Using aerial images with 50 cm spatial resolution, Pitkänen (2001) identified individual trees by combining binarization and local maxima procedures. When binarization methods and no binarization were applied to eight stands, overall accuracies varied from 50 to 96%. Tiede et al. (2005) developed an algorithm using laser scanning data and a local maxima method to identify trees in aerial images from a forest. A local maxima method was applied resulting in 51% of the trees identified; higher accuracies were achieved (>92%) when tree height was more than ten meters. Pitkänen (2001) found that low spatial resolution was a limiting factor for tree crown identification. However, Uuttera et al. (1998) stated that the requirements of spatial resolution for forestry applications are low, although specific values were not provided. The canopy width for container-grown nursery plants is smaller than that for forest trees, suggesting the need for higher spatial resolution images. Factors such as: similarities between spectral signatures, spatial distribution of features, and imagery spatial resolution could complicate the classification process. Once the camera resolution is fixed, spatial resolution can be increased by lowering the altitude at which images are taken. Also, spectral signatures of the ground cover used at nurseries or seasonal changes in the foliage color may influence the ability to differentiate plants from the background. Nursery growers require count data to be updated more frequently than foresters since the production cycle is shorter and crops change more frequently due to removal of plants from production blocks as a result of plant death, sub-grade plants, and shipping. Methods used to count forest trees may be useful in counting nursery crops.

Aerial images may be obtained by a variety of platforms such as balloons, kites and aircrafts (Aber, et al., 2002; Shellito, 2012). In order to automate plant counting, access to timely images with medium to high resolution are required. Unmanned aerial vehicles (UAVs) are increasingly being used in agricultural applications (Thomson and Sullivan, 2006; Furfaro et al., 2007; Grenzdörffer et al., 2008; Berni, et al., 2009; Dunford, et al., 2009; Ramezani Ghalenoei et al., 2009; Techy et al., 2010; Aylor, et al., 2011; Garcia-Ruiz et al., 2013; Torres-Sánchez et al., 2013). UAVs offers several advantages when used on agricultural applications including: vertical take-off and landing, on demand capability, customizable resolution, implementation of a flight plan using GPS coordinates, and automatically gyro compensated system to maintain the camera parallel to the ground (Ehsani and Maja, 2011).

Recent development of object-based image analysis (OBIA) software permits geospatial analysis and processing from images for features such as vegetation, roads, buildings, rivers and lakes. One example is Feature Analyst® (FA) (Overwatch System Ltd. Austin, Texas) (Visual Learning Systems, Inc, 2004; Riggan and Weih, 2009). FA is a software plug-in for Esri ArcGIS®, Overwatch's ELT/5500® and Global Image Viewer® software, which means that a license for any of these additional software must be purchased in order to use FA. FA has been used in land cover classification (Blundell et al., 2008; O'Brien, 2003) and impervious feature classification (Lavigne et al., 2006). In general, FA functions by segmenting individual objects into vector boundaries using a 'sample' created by the user; data from the 'sample' (e.g. spectral values and spatial data) are then correlated with target objects (Blundell and Opitz, 2006). MATLAB is a high-level language and interactive environment for technical performances and scientific computation (Selinummi et al., 2005; Agrawal et al., 2010). MATLAB is more popular, easier and intuitive to use than other programming packages such as C/C++ (Haldar et al., 2001). Image processing tools within MATLAB have been used in several applications such as identifying proteins (Tiwari et al., 2005), measuring fluvial gravels (Graham et al., 2005), license plate recognition (Cheng-qun, 2008), and monitoring fish health (Xingqiao et al., 2009). Additionally, MATLAB has been used to count objects such as coins (Sharma, 2014), grains (Peng et al., 2009) and plants (She et al., 2014). MATLAB program allows the operator to generate stand-alone executables that can be run outside MATLAB environment without requiring a network license to run the program. Thus, no recurring cost would be involved for running a MATLAB executable program. This research aims to explore image processing algorithms within MATLAB for inventory management of nursery plants.

Several factors contribute to the complexity of imagery used for plant inventory analysis including plant characteristics (plant color, species, plant size and shape, canopy cover, plant health), ground/surface characteristics (bare soil, gravel, ground cloth), and environmental factors (sunlight/shadows). Because these factors could influence the data obtained from remote sensing images, these conditions must be accounted for when using these images. In the United States, container-grown plants are typically produced on black fabric or native gravel, therefore, these two background were evaluated in this study.

The objective of this research was to evaluate the effect flight of altitude of a UAV and plant canopy separation on the counting of container-grown Fire Chief^{TM} arborvitae (*Thuja occidentalis* L.) grown on two different ground covers using two object-based methods.

Materials and Methods

Aerial Platform

The eight bladed (octocopter) UAV was assembled using components from MiKroKopter-US (Watsonville, CA), as described in Garcia-Ruiz et al. (2013). The UAV has a navigation system that accepts GPS waypoints (a reference point used for purposes of navigation) that were preloaded before flight. The operator manually triggered the on-board camera from the ground using an infrared remote. The UAV system, including remote control, cost approximately US $ 7500.

Initially four flight altitudes were proposed for evaluation: 6, 12, 18, and 24 m using the 'altitude hold' function of the UAV. However, when these experiments were conducted it was determined that the altitude hold function was not maintaining the UAV at a stable altitude. The reason for this problem was not known at that time. As a result of this unexpected instability and challenges in holding a known altitude manually, we decided to conduct the experiments at three flight altitudes: 6, 12, and 22 m.

Sensor

An off-the-shelf camera was used to evaluate its usefulness for obtaining inventory control information. A Sony NEX-5n (Sony Corporation of America IR, San Diego, CA) 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, and 4 bits/pixel. Autofocusing and aspect ratio of 3:2 were fixed. Flash, object tracking, and face detection were turned off. Images from this sensor contain three bands: red, green and blue. Sensor cost was US $ 750.

Experimental design

Experiments were conducted at Greenleaf Nursery, Park Hill, OK (Latitude: 35.779098, Longitude: -94.904323). Plants used to create training and treatment blocks were obtained from productions blocks at the nursery. Container-grown plants 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) (Fig. 2.1). Fire Chief™ arborvitae (*Thuja occidentalis* L.), growing in #3 black polyethylene containers (height: 23.5 cm, top diameter: 26.5 cm, and bottom diameter: 23.0 cm) (Plastics Inc., Jacksonville, TX) was used in the study since it was available in large numbers and has a regular shape. Plants were pulled from production blocks at the nursery. For each canopy separation treatment, a set of 64 containers (8 × 8) was established outdoors on gravel on 13 July, 2013 and on a black polypropylene ground cover (Lumite, Inc., Alto, GA) on 14 July, 2013. Since the same canopy separation treatments were used in both experiments, after images were taken on 13 July 2013, the same plants were repositioned onto black polypropylene ground cover. The number of plants used to create treatment sets were selected in order to mimic nursery production blocks and decrease edge effects. Sets with the three canopy separation treatments were replicated three times for a total of nine sets of treatment plants. One overlapping treatment set (-5 cm) only had 56 plants since nursery employees inadvertently pulled one row of plants between the set-up day and the day images were taken. These missing plants were not noted until images were later processed. Four fully separated plants were positioned outside the east edge of the nine sets and were used to train the MATLAB® (MathWorks Inc., Natick, MA) (MATLAB) algorithm. This algorithm was written by a graduate student at the University of Florida, Gainesville, FL and the number of training plants required was determined by user experience (further details regarding algorithm training will be presented later). Other uses for this algorithm are described by She et al. (2014). Three additional sets of 49 containers (7 × 7) representing the three canopy separation treatments were positioned adjacent to the treatment sets and were used to train the algorithm using FA, and henceforth referred to as training sets (Fig. 2.2). Plant number in training sets were smaller than treatment sets to represent a sample of the whole treatment set. The number of plants used to create training samples using FA was initially determined to be eight plants, however, depending on extraction results, all 49 plants could be used (further details regarding algorithm training will be presented later).

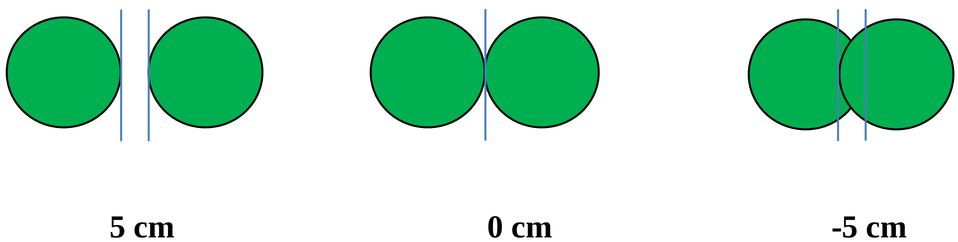

Fig. 2.1. Representation of canopy separation treatments.

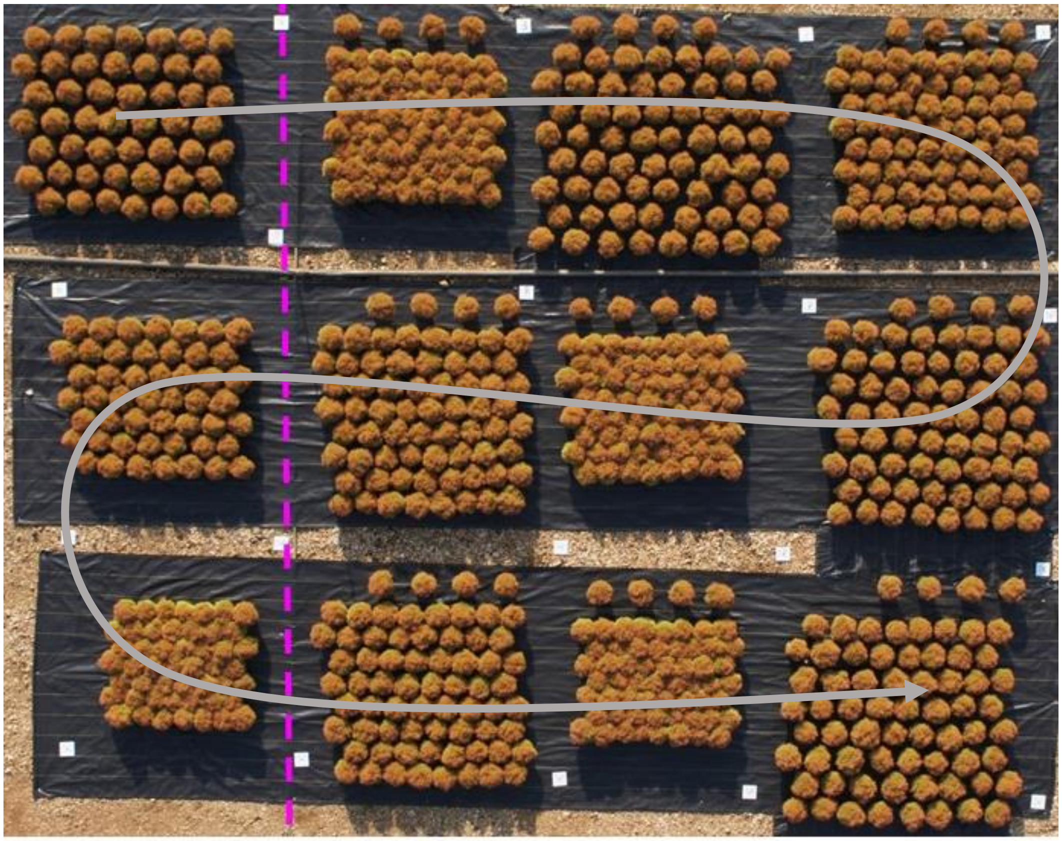

Fig. 2.2. Aerial image of the experimental layout. The gray line represents the flight path or run for the UAV.

Five plants per set were used for plant measurements. These were four corner plants and one plant located diagonally adjacent to the southwest corner plant. Shoot height was measured from the substrate surface to the top of the plant. Average shoot height was 26.2 cm. Average shoot diameter was determined by taking two measurements at 90° from each other. Average shoot diameter was 36.9 cm. Red, green and blue digital number (RGB) mean values were calculated from an aerial image at 0.52 cm/pixel spatial resolution, under sunny conditions using eCognition (Trimble©, Westminster, CO) for plant canopy and ground covers. RGB mean values were calculated using the process flow diagram presented in Fig. 2.3.

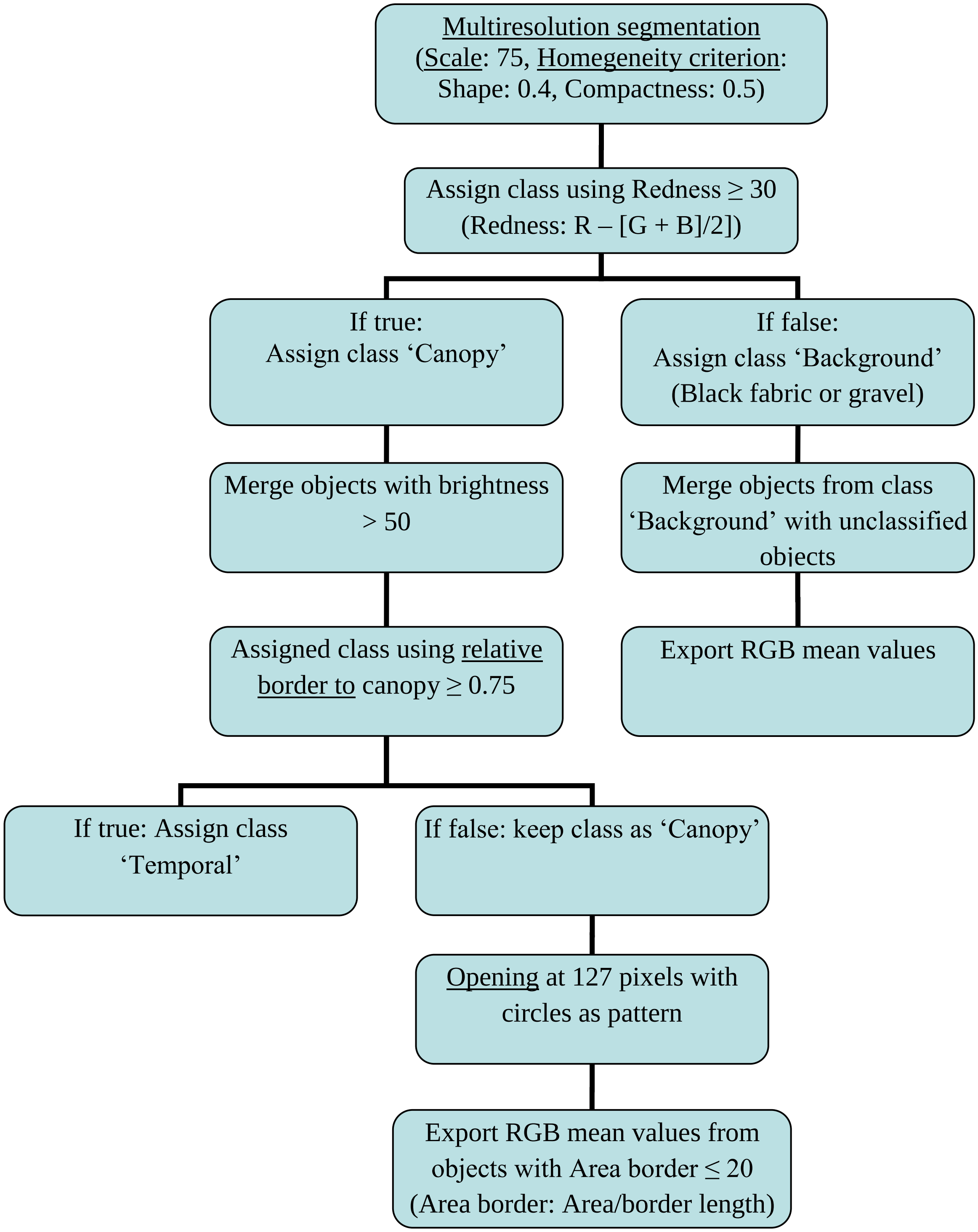

Fig. 2.3. Representation of rule set developed in eCognition® to calculate RGB mean values for canopy and background.

Figure 2.4 shows the output image for the class 'Canopy, after the rule set is run, as a result of the last rule applied in Fig. 2.3. A CSV file is generated with mean values of individual objects and used to calculate RGB mean values for each class in Microsoft Excel® (Microsoft©, Redmond, WA). RGB mean values resulted in 174±6, 123±5, 63±3 for Fire Chief™ arborvitae canopies, 77±39, 77±38, 80±35 for black fabric and 183±41, 149±42, 113±41 for gravel. The image was taken using the same camera used for all images with an f value = 8, shutter speed= 1/320 seconds taken at 0930. Other settings were the same as previously described.

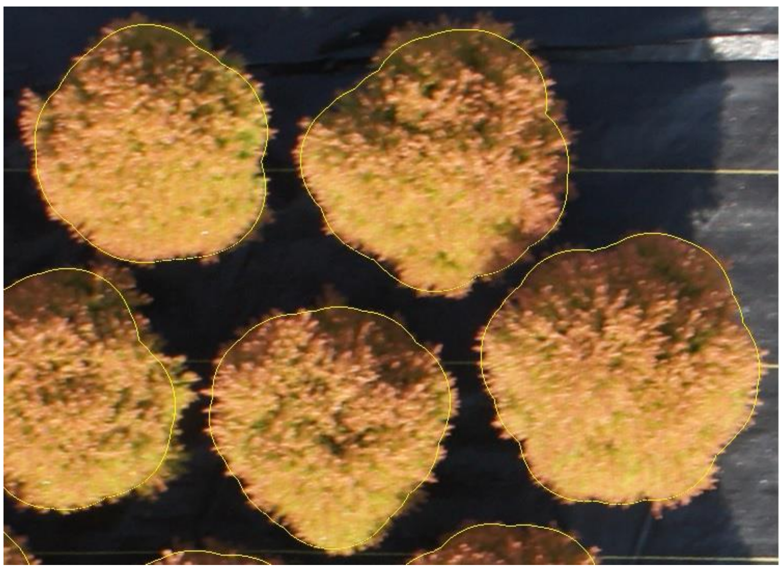

Fig. 2.4. Objects classified as 'Canopy' using eCognition®.

Images were obtained using a UAV flown at three altitudes (6, 12, and 22 m) above the treatment sets. The same flight path (Fig. 2.2) was used for each altitude and the three flight altitudes were executed two times, henceforth, referred to as a run. Flight altitudes were randomized within each run. The altitude factor was arranged as a randomized complete block design with two blocks and three altitudes. The blocks for the canopy separation factors were nested within the runs. At least two images were taken of each set of plants. Image spatial resolution was calculated based on square white boards (20 × 20 cm) positioned around the treatment blocks.

When FA was used, three variables were quantified manually by the operator using the final count and output image as follows:

Total count error: total software count – ground count. Error was also represented as percentages based on the ground count from the set.

False positives: counts that do not represent a target plant (e.g. multiple counts or other objects within the ground cover that were counted as a plant). No weeds were present in the experimental area.

Unidentified plants: target plants that were not counted.

Means were separated using an analysis of variance followed by a Tukey-Kramer test based on the experimental design described above using SAS 9.3 (SAS Institute Inc., Cary, NC). No statistical comparison was made between results obtained using the two software packages. The objective of this research was not to compare algorithm performance as plants change over time.

Light intensity, relative humidity, temperature, and ground wind speed were measured using a Mini Environmental Quality Meter (Sper Scientific, Scottsdale, AZ) (Table 2.1). A subjective estimate of cloud cover was recorded for each flight using the following scale: clear, <5% cloud cover (CC); partly cloudy, 5-50% CC, mostly cloudy, 51-95%; and overcast, >95% CC (Table 2.1). While remote sensing data are recommend to be obtained around noon we chose to fly earlier to avoid higher winds forecast for this location. As a result, flights were started at

0800. Images obtained presented shadows over the plant canopies, however, these shadows were also present in the training set images used to train the algorithm. Processing of images and algorithm training will be discussed in a later section.

Table 2.1. Environmental parameters measured before UAV flights at three altitudes

	Flight altitude (m)	Time CST	Wind Speed (km/h) Min.	Max	Light Intensity (LUX)	RH (%)	CC[y] (%)	Temp. (°C)
Black fabric	22 (1)[z]	0800	0.6	3.0	97	62	<5%	27.5
	12 (1)	0820	0.7	7.8	125	61	<5%	28.1
	6 (1)	0835	0.0	4.5	130	58	<5%	28.5
	6 (2)	0845	0.0	10.8	150	59	<5%	28.8
	12 (2)	0905	0.0	6.7	166	55	<5%	30.4
	22 (2)	0930	0.7	5.8	159	57	<5%	30.9
Gravel	6 (1)	0740	0.0	0.0	83	72	<5%	28.0
	22 (1)	0850	0.0	3.5	130	59	<5%	31.5
	12 (1)	0905	0.0	3.1	170	54	<5%	33.0
	22 (2)	0930	0.0	5.0	177	52	<5%	34.0
	12 (2)	0955	1.0	6.1	186	51	<5%	35.0
	6 (2)	1035	0.7	9.0	166	50	<5%	35.3

[z]Number in parenthesis indicates the run number.
[y]Cloud cover visual rating: cloud cover: <5%, 5-50%, 50-95%, >95%

Image selection

One image per set was selected using the following criterion:

- The experimental unit must be completely displayed within the image. The four fully separated plants on the east side of the set must be displayed within the image. Due to unexpected issues previously mentioned, some images, did not capture completed experimental units, and therefore, were not used to evaluate algorithm accuracy.
- Priority was given to images with the most centered treatment set.

In order to decrease image processing time, images were cropped and rotated using Adobe Photoshop Elements 6 (Adobe System Incorporated, San Jose, CA) leaving only the set of interest for that particular image.

Algorithm training using Feature Analyst®

A total of 18 AFE models were created, one for each variable (three canopy separation × three flight altitude × two runs = 18); however, only one algorithm was applied to each canopy separation treatment set at a single flight altitude (e.g. when an algorithm is trained from an image taken at 6 m of a training set with a canopy separation of 5 cm, that algorithm is then applied to images with a similar canopy separation taken at the same flight altitude from one run). The general process of training an algorithm was as follows. Images were added into ArcMap™ Version 10.1 (ESRI, Redlands, CA) in JPEG format without being geo-referenced. Circular shapes ('samples') were digitized over individual plants. Several shapes can be used to digitize samples, however, circles were used since they require less user input than customizable polygons, making the process faster and more reproducible (Fig. 2.5). The initial number of circular shapes digitized was based on user experience and their position within the image was selected in order to capture variability of the target plants. For all algorithms the initial number of digitized circles was eight, and their positions are shown in Fig. 2.6. These positions were selected in order to capture distortion within the image which tends to be more variable at the edge of the images.

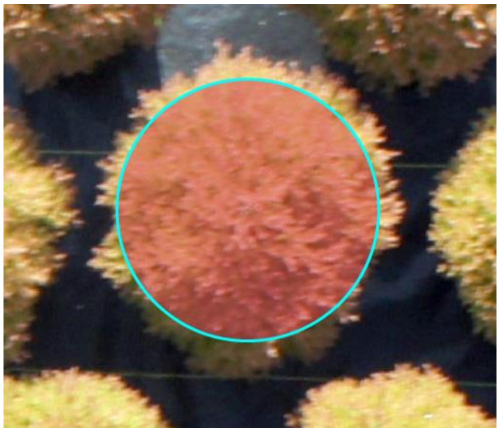

Fig. 2.5. Digitized circular sample used to extract plant canopies using Feature Analyst®.

Fig. 2.6. Initial positions of digitized circular samples in a training image using Feature Analyst®.

A first segmentation based on the digitized samples was run using a supervised learning approach with the following parameters: a nature feature selector, no resample factor, Manhattan input representation and vector as the output format. All three color bands were used for algorithm training. Based on the results from the first segmentation, pattern width of the input representation and/or number, size, and position of digitized circles might be modified until a uniform segmentation was obtained; a similar procedure was used by Hamilton et al. (2009), Miller et al. (2009), and Caley et al. (2011) in wildlife, urban application, and rhizotron measurements, respectively. Following this, a number of procedures were applied to the image. These procedures included: conversion from raster to vector and vector to raster formats, aggregation, erosion, dilation, opening, smoothing, calculation of vector metrics and conversion from polygons to points. Some of these procedures were applied more than once. Parameters for those procedures were fixed according to the images used for training. After the last procedure was applied (conversion from polygons to points), FA creates an 'automated feature extraction' (AFE) model that stores training set data and all procedures applied. Finally, the trained algorithm was applied to treatment images displaying the same canopy separation and flight altitude. The algorithm was applied to the respective treatment set images using the AFE model and the batch processing tool.

Parameters used to train the algorithm were based on user experience and a subjective analysis of the output files after procedures were applied. Parameters such as the number of cycles that a procedure is applied was c hanged several times by the operator until the final plant count no longer increased for that specific training image. This may be a source of error since different users might consider different procedures, order of procedures, and parameters.

Algorithm training using MATLAB

A counting algorithm was written using MATLAB based on the assumption that canopy area of container-grown plants within the area of interest varies little. The algorithm was developed based on the canopy area for four plants positioned outside the treatment blocks and later applied to the treatment blocks to estimate the number of plants. Canopy area is defined as the mean number of total pixels for training plants in the image. The trained algorithm mainly relies on color and texture information to extract and analyze plants. Different color information was used to extract plants from gravel and black fabric ground covers. Main steps in training the algorithm are as follows.

Step 1: Extraction of training plants

Based on the foliage color for the plant used in this project, a normalized index (Red - Green)/(Red + Green) was used to extract the plants and then convert the image to binary. In the resulting images white pixels represent plants and black pixels represent ground cover (Fig. 2.7).

Fig. 2.7. Extraction of training plants using the MATLAB algorithm.

Step 2: Estimation of canopy area

Morphology tools (erosion followed by dilation) were applied in order to improve extraction results. For the gravel ground cover, further processing was required due to the presence of falsely identified pixels within the ground cover (Fig. 2.8) that were subsequently deleted using an area threshold set according to image resolution (Fig. 2.9). Average plant canopy area was calculated based on the area of the remaining white regions.

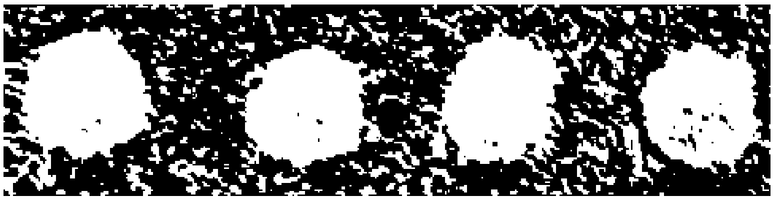

Fig. 2.8. Training plants with falsely identified pixels.

Fig. 2.9. Training plants after morphology tools were applied. The smallest area of white pixels was removed by area thresholding.

Step 3: Extraction of container-grown plants from treatment blocks

For images using black fabric ground cover, normalized index [(Red -Green)/(Red + Green)] was applied to extract plants (Fig. 2.10). Images with gravel ground cover presented a larger number of falsely identified pixels as plants, therefore, these pixels were eliminated using two approaches: 1) morphology tools, and 2) thresholding on the average plant canopy area (used to remove relatively large regions but smaller than actual canopy areas). Pixels that lie between plant canopies that connect two or more adjacent plants created an even larger area of white pixels (Fig. 2.10). Since this scenario cannot be solved by the two previously mentioned methods, a 'dark index' was created [3-(Red + Green + Blue)-30*(ABS(Red-Green))] to extract the dark pixels between adjacent plants. The image that results from the 'dark index' (Fig. 2.11) is superimposed onto the image which was created according to the normalized index (Fig. 2.10).

This process helps remove falsely identified pixels between adjacent plants, as shown in Fig. 2.12.

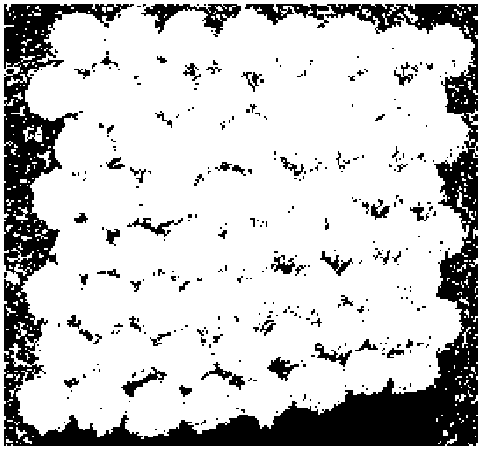

Fig. 2.10. Falsely identified pixels connecting adjacent plants.

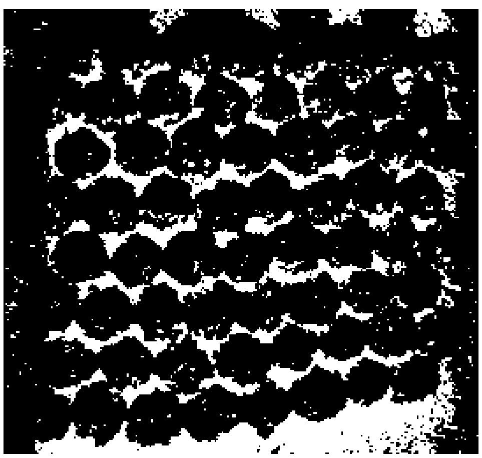

Fig. 2.11. Resulting image after 'dark index' was applied.

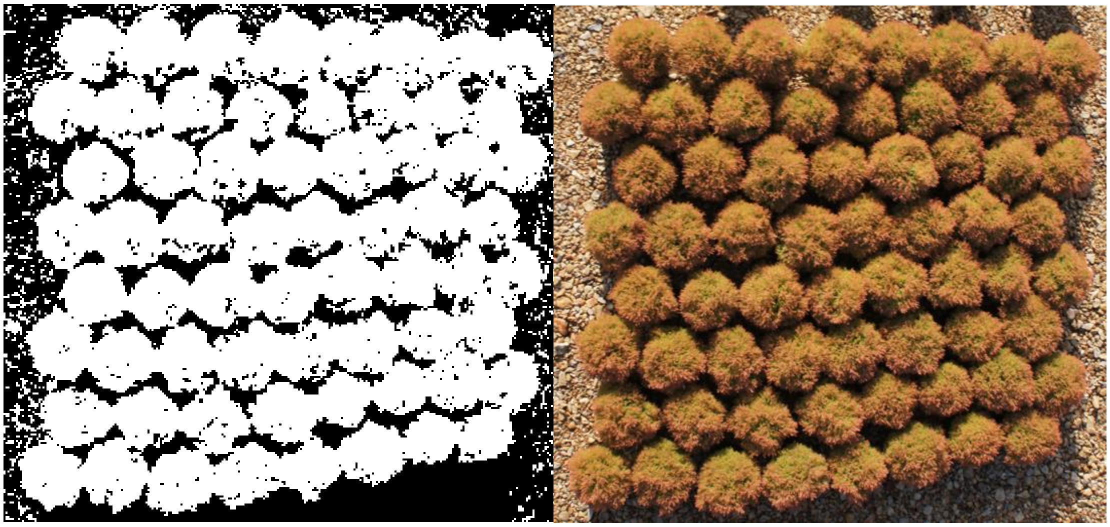

Fig. 2.12. Left: Resulting image after modification. Right: True composite image.

Step 4: Use calculated canopy area from training plants (A) to count plants in treatment blocks

In the final calculation, an 'if then' statement was used. If the area of white pixels in the treatment set images were smaller than 0.5 $\times$ A, then it was not counted as a plant. If the area of white pixels lay within the range of 0.5 $\times$ A and 1.0 $\times$ A, it was counted as 1 plant. If it was in the range of 1.0 $\times$ A and 2.0 $\times$ A, it was counted as 2, and so on. The process continues until all white regions were included.

When canopies were overlapping (-5 cm) and plants were placed on gravel, a correction ratio was applied to improve the algorithm count. This correction ratio (manual count/algorithm count) was calculated using the images from overlapping treatments placed on black fabric.

eCognition

When the original research was proposed, images were to be analyzed using a third object-based software program, eCognition. After spending significant time trying to become proficient with this software and relying on help from faculty at the Center for Advanced Spatial Technologies (CAST) at the University of Arkansas, and technical service staff at Trimble, it was determined that this software could not be used at this time.

Results and discussion

Since one of the overlapping treatments sets had 56 plants instead of 64, data were statistically analyzed using:

a) All data (including observations where the ground count was 56), and

b) Data excluding observations where the ground count was 56

Both approaches resulted in the same mean separation, therefore, all data are presented. There were three replicates for overlapping treatments and two runs, for a total of 6 observations, resulting in an average ground count of 61 for this treatment set.

Ground cover: black fabric

Significance for main effects and the interaction among factors related to total count errors, false positives and unidentified plants analyzed with FA and MATLAB when plants were placed on a black fabric ground cover are shown in Table 2.2. Flight altitude was not significant for any variable measured. There was no significant effect of canopy separation on total count error using FA when images were taken at 12 or 22 m (Table 2.3). When images were taken at 6 m, there was a significant difference in total count error between plants with canopies that were touching (0 cm) and overlapping (-5 cm); an undercount (-20% count error) was observed when canopies were touching and an over count (26% count error) when they were overlapping. The highest total count error expressed as percentage (26%) was observed for images taken at 6 m of plants with overlapping canopies. Treatments with total count errors between -4 and 2 are not significantly different from zero; this includes all treatments where the canopy separation was 5 cm regardless of flight altitude. Since part of the algorithm's training is pixel classification, the level of detail in high resolution images (e.g. 6 m flight altitude) may cause an increase in counting errors. Cushnie (1987) suggested that increasing spatial resolution could complicate land cover classification process due to an increase in spectral signature variability. Ayyalasomayajula et al. (2009) found count errors ranging from -27.17% to 23.00% using 15 cm spatial resolution images when analyzed using FA to count citrus trees. Tree crown delineation has been achieved using different methods and input data with accuracies ranging from 48% to 92% (-52 to -8% count error) (Pouliot et al., 2002; Leckie et al., 2003; Bunting and Lucas, 2006), but forest complexity is much greater than nursery settings due to diversity of tree species and tree ages.

Table 2.2. ANOVA for variables measured when counting container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on a black fabric ground cover using Feature Analyst® (FA) and MATLAB®.

Source	Total count error[z] (FA)	False positives[y] (FA)	Unidentified plants (FA)	Total count error using MATLAB®
Flight altitude	NS	NS	NS	NS
Canopy separation	*	*	*	*
Flight altitude × Canopy separation	*	*	NS	NS

*, NS indicate statistical significance at the 0.05 probability level and not significant, respectively.
[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64, except for the set with a canopy separation of -5 cm, where the average ground count was 61.
[x]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were counted as a plant).

Table 2.3. Total count error for container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on a black fabric ground cover using Feature Analyst®

Canopy separation (cm)	Flight altitude (m)					
	6		12		22	
	No.[z]	%[y]	No.	%	No.	%
5	-3 ab[x]	-5%	1 ab	1%	0 ab	0%
0	-13 b*	-20%	-12 b*	-19%	-4 ab	-7%
-5	16 a*	26%	2 ab	4%	-7 b*	-11%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64, except for the set with a canopy separation of -5 cm, where the average ground count was 61.
[y]Total count error expressed as percentage; total count error/ground count × 100.
[x]Means followed by the same letter are not significantly different based on Tukey-Kramer's test ($F=3.30$, $p=0.0235$).
*Means significantly different from zero based on a t test ($p \leq 0.05$).

For FA, counts errors are based on the total count generated; further analysis was conducted to evaluate potential sources of error. With this in mind, false positives (counts that did not represent a target plant) and unidentified plants (target plants that were not counted) were identified in output images. False positive data are presented in Table 2.4. The largest percentage of false positive counts (44%) was observed for images taken at 6 m when canopies were overlapping (-5 cm). The number of false positive counts for images taken at 6 m when canopies were overlapping is significantly different from all other treatment means. Regardless of the flight altitude, total false positive counts for the overlapping canopy treatments were significantly different from zero. False positive counts likely occur when plant canopies are overlapping regardless of flight altitude because the aggregation parameter is fixed in the training algorithm, and when applied to images with different spatial resolution, some polygons not representing target plants are likely counted. Even at the same flight altitude, differences in spatial resolution (Table 2.5) occur because the UAV cannot hold a precise altitude. A large, positive total count error is most likely a result of a greater contribution from a large number of false positives than from unidentified plants.

Table 2.4. False positive counts for container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on a black fabric ground cover using Feature Analyst®

Canopy separation (cm)	Flight altitude (m)					
	6		12		22	
	No.[z]	%[y]	No.	%	No.	%
5	1b	2%	2 b	3%	1 b	2%
0	1 b	2%	1 b	2%	1 b	2%
-5	27 a*	44%	12 b*	19%	10 b*	16%

[z]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant).
[y]Percentages of false positives is based on the ground count from the set. False positives percent are based on a ground count of 64, except for the set with a canopy separation of -5 cm, where the average ground count was 61.
[x]Means followed by the same letter are not significantly different based on Tukey-Kramer's test ($F=3.31$, $p=0.0245$).
*Means significantly different from zero based on a t test ($p\leq0.05$).

Table 2.5. Spatial resolution of images taken at 6, 12 and 22 m flight altitudes using gravel and blacks fabric as ground covers

Flight altitude (m)	Spatial Resolution (cm/pixel)	
	Black fabric	Gravel
6	0.154±0.018	0.150±0.030
12	0.240±0.036	0.310±0.097
22	0.486±0.103	0.464±0.055

There was no significant interaction between flight altitude and canopy separation for unidentified plants when images were analyzed using FA; flight altitude was also not significant (Table 2.2). When FA was used to analyze images, the number of unidentified plants tended to increase as the canopy separation changed from fully separated (5 cm) to overlapping (-5 cm) (Table 2.6). The total number of unidentified plants when canopies were fully separated was significantly different from the unidentified plant count for the other canopy separation treatments. As discussed previously, total count errors (Table 2.3) were also affected by the number of unidentified plants, especially the large undercounts (negatives values). The number of unidentified plants occurs most when plant canopies are overlapping, and there may be several explanations for this. First, the algorithm has difficulty separating canopies because the polygon shapes where two or more canopies overlap are not distinct enough. This issue could not be resolved by applying an erosion procedure (Fig. 2.13). Secondly, because the aggregation parameter is fixed in the training algorithm and then applied to images with different spatial resolution, some target plants may be missed. Differences in spatial resolution occur because the UAV cannot hold a precise altitude. As a result of the high resolution images used in this study (Table 2.5), we did not encounter problems reported by other authors where they found it difficult to identify target objects below a specific pixel threshold (Madsen et al., 2011, Wulder et al., 2000).

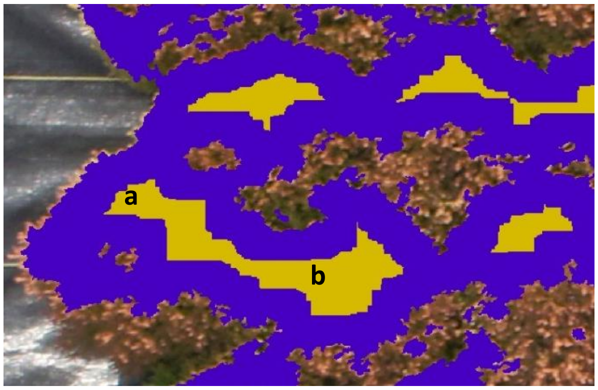

Fig. 2.13. Yellow polygons created by Feature Analyst® after a negative buffer was applied to blue polygons. Letters ‘a’ and ‘b’ represent the location of two different plants.

Table 2.6. Unidentified plants for container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on a black fabric ground cover and analyzed using Feature Analyst®

Canopy separation (cm)	Unidentified plants No.	% [z]
5	2 b[y]	3%
0	11 a*	17%
-5	13 a*	21%

[z]Unidentified plant percent are based on a ground count of 64, except for the set with a canopy separation of -5 cm, where the average ground count was 61. Data averaged over three flight altitudes: 6, 12, and 22 m.
[y]Means followed by the same letter within the same column are not significantly different based on Tukey-Kramer’s test (F=10.88, p=0.0001).
*Means significantly different from zero based on a t test (p≤0.05).

Total count errors generated by the MATLAB and FA algorithms for arborvitae plants placed on black fabric cover are shown in Table 2.7. FA data were re-analyzed considering canopy separation as the main effect (Table 2.2) so a non-statistical comparison could be made between software. For MATLAB, total count error was significantly different between the three canopy separation treatments. From a percentage standpoint, the smallest (-5%) count error was observed when canopies were touching (0 cm) and highest (-28%) when canopies were overlapping (-5 cm). On the other hand, results using FA showed a significant difference in total count error between overlapping and touching canopy treatments (Table 2.7). When comparing count error percentages only, results using FA were smaller than MATLAB when canopies were fully separated and overlapping.

Table 2.7. Total count errors for container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on a black fabric ground cover using MATLAB® and Feature Analyst® (FA)

Canopy separation (cm)	MATLAB®		FA	
	No.^{z}	%^{y}	No.	%
5	4 a^{x}	6%	-1 ab^{x}	-2%
0	-3 b	-5%	-10 b*	-16%
-5	-17 c*	-28%	4 a	6%

^{z}Total count error: total software count – ground count. Total count errors are based on a ground count of 64, except for the treatment with a canopy separation of -5 cm, where the average ground count was 61. Data averaged over three flight altitudes: 6, 12, and 22 m.
^{y}Total count error expressed as percentages; total count error/ground count × 100.
^{x}Means followed by the same letter within the same column are not significantly different based on Tukey-Kramer's test [MATLAB (F=94.95, p<0.0001); FA (F=5.64, p=0.0146)].
*Means significantly different from zero based on a t-test ($p \leq 0.05$).

Ground cover: gravel

Significance for main effects and the interaction among factors related to total count errors, false positives and unidentified plants analyzed with FA and MATLAB when plants were placed on gravel as ground cover are shown in Table 2.8. When data were analyzed using a Tukey-Kramer test, the only significant differences were for -5 cm canopy separation at 12 m and 0 cm canopy separation at 12 m (Table 2.9). The following treatment means for total count error were different from zero and presented the highest total count errors: canopies touching and overlapping at 6 m and canopies touching at 12 m. In general, for images taken at 22 m, total count error between canopy separation treatments is fairly similar. Total count errors tend to be greatest when images are taken at 6 and 12 m for touching and overlapping canopy treatments.

Table 2.8. ANOVA for variables measured when counting container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on gravel as ground cover using Feature Analyst® (FA) and MATLAB®.

Source	Total count error^z (FA)	False positives^y (FA)	Unidentified plants (FA)	Total count error (MATLAB®)
Flight altitude	NS	NS	*	NS
Canopy separation	NS	*	*	NS
Flight altitude × Canopy separation	*	*	*	NS

*, NS indicate statistical significance at the 0.05 probability level and not significant, respectively.
^zCount error: total software count – ground count. Total count errors are based on a ground count of 64, except for the set with a canopy separation of -5 cm, where the average ground count was 61.
^yFalse positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant).

Table 2.9. Total count errors for container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on gravel as ground cover using Feature Analyst® (FA)

Canopy separation (cm)	Flight altitude (m)					
	6		12		22	
	No.^z	%^y	No.	%	No.	%
5	0	0%	-4	-6%	-5	-8%
0	-27*	-42%	-23*	-36%	1	2%
-5	-29*	-47%	13	21%	3	5%

^zTotal count error: total software count – ground count. Total count errors are based on a ground count of 64, except for the set with a canopy separation of -5 cm, where the average ground count was 61. The following pairs are significantly different: -5 cm canopy separation at 12 m and 0 cm canopy separation at 12 m (F=5.72, p=0.0018).
^yTotal count error expressed as percentages; total count error/ground count × 100.
*Means significantly different from zero based on a t test (p≤0.05)

False positive count means generated by FA when plants were placed on gravel are presented in Table 2.10. The only significant differences were observed for images taken at 12 m for the following pairs: canopies overlapping (-5 cm) and touching (0 cm), and canopies overlapping and fully separated (5 cm). Only one false positive count mean was different from zero and this was for images taken of overlapping canopies at 12 m.

Table 2.10. False positive counts for container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on gravel as ground cover using Feature Analyst® (FA)

Canopy separation (cm)	Flight altitude (m)					
	6		12		22	
	No.[z]	%[y]	No.	%	No.	%
5	3	5%	1	2%	1	2%
0	0	0%	5	8%	3	5%
-5	3	5%	26*	42%	14	23%

[z]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant). The following pairs are significantly different: 12 m at -5 cm canopy separation and 12 m at 0 cm canopy separation; 12 m at -5 cm canopy separation and 12 m at 5 cm canopy separation ($F=3.55$, $p=0.0141$).
[y]Percentages of false positives are based on the ground count from the set. False positives percent are based on a ground count of 64, except for the set with a canopy separation of -5 cm, where the average ground count was 61.
*Means significantly different from zero based on a t test ($p\leq0.05$).

Unidentified plant count means generated by FA when plants were placed on gravel are shown in Table 2.11. Regardless of the canopy separation treatment, there was no significant difference in unidentified plant means when images were taken at 22 m. In general, for canopy treatments touching and overlapping, the number of unidentified plants decreased significantly as the flight altitude increased from 6 to 22 m when canopies are either touching or overlapping. Unidentified plants were not significantly different from zero when canopies overlap (-5) in images taken at 6, 12, and 22 m, and when canopies are touching (0 cm) at 22 m. A similar trend was observed in total count error means (Table 2.9).

Table 2.11. Unidentified plants for container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on gravel as ground cover using Feature Analyst® (FA)

Canopy separation (cm)	Flight altitude (m) 6		12		22	
	No.[z]	%[y]	No.	%	No.	%
5	3 c	5%	4 c	6%	6 bc	9%
0	27 ab*	42%	29 ab*	45%	3 c	5%
-5	31 a*	51%	14 abc*	23%	10 bc*	16%

[z]Means followed by the same letter are not significantly different based on Tukey-Kramer's test (F=4.81, p=0.0042).
[y]Unidentified plant percentages are based on a ground count of 64, except for the set with a canopy separation of -5 cm, where the average ground count was 61.
*Means significantly different from zero based on a t test (p≤0.05).

Total count errors for the total count generated by MATLAB when plants were placed on gravel are shown in Table 2.12. There was no significant difference between treatments (F=0.47, p=0.7571); all means were not significantly different from zero.

Table 2.12. Total count error for container-grown Fire Chief™ arborvitae (*Thuja occidentalis* L.) on gravel as ground cover using MATLAB®

Canopy separation (cm)	Flight altitude (m) 6		12		22	
	No.[z]	%[y]	No.	%	No.	%
5	1	2%	2	3%	3	5%
0	-2	-3%	-5	-8%	0	0%
-5	2	3%	0	0%	2	3%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64, except for the treatment with a canopy separation of -5 cm, where the average ground count was 61.
[y]Total count error expressed as percentage; total count error/ground count × 100.

Although a direct statistical comparison was not made between count results for images analyzed with FA and MATLAB, the following statements are made. FA showed a smaller overall total count error (-2) than MATLAB (-5) when plants were placed on a black fabric ground cover (total count errors averaged over all flight altitudes and canopy separation treatments). Even though both methods (MATLAB and FA) use canopy area in algorithm training, FA is more adaptable since it uses other attributes (e.g. color). This conclusion is based on count accuracy results from both methods when black fabric was used as the ground cover. On the other hand, when plants were placed on gravel, MATLAB resulted in a smaller overall mean total count error (1) than FA (-8). It should be noted that a correction ratio for images with overlapping canopies was applied in the MATLAB algorithm for plants on a gravel ground cover; this ratio was calculated using the data from images of plants with overlapping canopies placed on black fabric. Since only the MATLAB method uses this correction ratio makes it difficult to compare results between the two methods.

When images were analyzed using FA, total count error (at all flight altitudes and canopy separation treatments) for plants placed on gravel (-8) was larger than for plants placed on a black fabric (-2), however, false positive counts were similar for black fabric (6) and gravel (6) ground covers. Since false positive counts were not different between ground covers, total count errors are more likely to be affected by unidentified plants, which was smaller for plants placed on a black fabric (9) than those placed on gravel (14). Nevertheless, output images of plants placed on gravel did not appear to be affective by the ground cover; in general, higher total count errors might be caused by larger differences in image <u>spatial resolution</u> for plants placed on gravel (Table 2.6). When MATLAB was used, total count error was higher when plants were placed on black fabric (-5) than gravel (1). The correction ratio calculated from images when black fabric was used, may explain why total count error was better.

In general, for both methods (FA and MATLAB), counting results were better when plants were fully separated. Shank (2009) concluded that FA has the potential to extract trees from aerial images when individual trees and shrubs were sufficiently separated from each other at a spatial resolution of 2.4 m; trees proximal to other trees, trees forming conglomerates, and trees underneath larger trees were stated as sources of error. In this study using Fire Chief^{TM} arborvitae, when plant canopies were overlapping, there is not enough difference in feature properties individual canopies, making it difficult for FA and MATLAB to isolate individual plants.

There are several reasons that contribute to the variability of the results observed. Likely the most important factor in this experiment was the inability to hold a consistent flight altitude for the UAV which ultimately affects spatial resolution. Also, even slight deviations of the camera angle relative to the ground impacts spatial resolution. Segmentation results are affected by the spatial resolution of the digitized 'samples'. Keeping in mind that spatial resolution varies within a single image (radial relief displacement), 'samples' might not represent all target objects, hence, decreasing segmentation quality and count accuracy. As expected, digitized 'samples' will vary even more between 'samples' and targets objects in different images.

Each method has its advantages and disadvantages. The algorithms trained in MATLAB uses training plants in the same image as treatment plants which results in the spatial resolution between the two sets of plants being similar and also allows adding new tools like the correction ratio previously mentioned. FA uses different images for training and treatment sets. Differences in spatial resolution between training and treatment images, and between treatment images, are likely to decrease count accuracy when using FA. The batch processing tool in FA allows the operator to process several images at the same time using one AFE model. In contrast, MATLAB algorithm requires the operator to set an area parameter for every image to be analyzed, however, the counting process is faster.

Different exposures and ISO values generated by the intelligent auto setting of the camera will cause a variation in the segmentation results. However, as mentioned before, the variation in those variables was minimal. Although not reflected in the image metadata, light intensity was different every time a run was executed (Table 2.1). Exposure values are slightly different between images, which might increase the experimental error. In order to fix exposure values, manual shooting mode should be used. For these experiments, intelligent auto shooting mode was selected based on preliminary experiments conducted at Lake Alfred, FL.

Training and treatment images were taken during a single day and there were minimal differences in light intensity (e.g. full sun, cloudy) between training and treatment sets. If images were taken on different days (i.e. replicated over longer time frame), it is possible that light conditions between training and treatment sets would be different.

While repeating experiments over time would mean that results might apply over a wider range of environmental conditions, for these experiments, it was not possible due to several practical reasons. First, these experiments were conducted at a large commercial nursery and requisite plants were borrowed from production blocks. It is a significant hardship on the nursery to move large numbers of experimental plants and to occupy an experimental area for very long. Secondly, although Greenleaf Nursery is considered a large wholesale nursery, identifying a suitable research plant of sufficient numbers was difficult. For example, the original plant desired for these experiments was Mr. Bowling Ball™ arborvitae (*Thuja occidentalis* L. Mr. Bowling Ball™) since it has the ideal canopy shape and color for these experiments. However, it was not available in a large enough quantity (300 available when 800 required). A possible solution to these smaller plant numbers would be to reduce the size of training and treatment sets. However, this compromises the quality of the data due to edge effects from smaller sized blocks. An objective in establishing treatment block size was to also consider a practical relationship to typical production block sizes in the nursery. For these reasons, Fire Chief™ was finally selected, although its foliage color was not green. Based on the rapid turnover of plant material in the nursery it is very unlikely that 800 Fire Chief™ of a similar size would be available if the experiment were to be repeated later in time. This demonstrates the challenge in conducting these studies over time which involve large numbers of similar plants. For subsequent experiments, the number of blocks was increased from three to five, which increased the number of plants required to improve data quality.

As it relates to these experiments, environmental parameters such as light conditions cannot be evaluated using the methods applied to these images, since a single training set is used to count different plants. Therefore, the algorithms may not be able to count plants accurately in images with large differences in RGB mean values generated by differences in light conditions within treatment and training images. If the question being asked is, “Does the performance of the algorithm change over time?” it would require a different experimental design or replication of this design on several different occasions. This alternative approach should account for changes in leaf color, canopy shape, canopy size, environmental parameters, and even more important, a consistent image spatial resolution. Replicating the experiment over time would mean that results would apply over a wider range of environmental conditions. Again, light exposure (i.e. full sun versus cloudy) was fairly consistent in these experiments enabling us to focus more on the question how do algorithms perform under a set of specific conditions. However, these studies were able to demonstrate over restricted conditions that the algorithms are able to count plants accurately when plant canopies were fully separated (5 cm) at the highest height evaluated (22 m), within the conditions previously described.

Results from these experiments are limited to the factors and conditions studied and may not be transferable to other plants and/or conditions.

Conclusions

In general, as the canopy separation and flight altitude of a UAV decreased, total count error increased. The observation that the lower flight altitude (i.e. higher image resolution) resulted in lower count accuracy was unexpected. A similar conclusion was reached in a preliminary experiment at Lake Alfred, FL in 2012 using *Arachis* sp. (She et al., 2014). Although count accuracy for plants placed on gravel was lower than those placed on black fabric, this was not related to ground cover type but more to do with variation in spatial resolution (Table 2.5) which was a result of the UAV not being able to hold a precise altitude. Although holding a constant altitude was difficult in these experiments, hardware and software is constantly being developed in order to improve UAVs flying capabilities. Consistency of spatial resolution is desirable since it assures a better result when algorithms are applied to different images. A UAV was used in these experiments as the platform to collect remote sensing images since it was thought to be the best option at that time, however, unexpected issues related to GPS-based navigation and general flight altitude stability were identified as a result of solar flare and geo-magnetic field interferences with the GPS unit. It should be noted that software and hardware updates for UAVs are continuously being developed which addresses many of the limitations identified. A UAV system with more precise automatic systems may prove useful to researchers and commercial operators in the future, but at this time this platform requires improvements in flight control systems.

FA is easy to use but several parameters had to be changed when training the algorithm requiring a great amount of time. While FA generated good counting results, MATLAB algorithm yielded better overall count accuracy for plants placed on gravel due to the addition of a correction ratio calculated from images for plants placed on black fabric. The use of the 'if then' statement when using the MATLAB method may not work well when plant canopy areas in a treatment set vary widely, although this would need to be evaluated to confirm. Updated versions of FA and the customizable algorithm trained in MATLAB are likely to improve future counting efforts. Based on results from this research, object-based methods should be based on metrics besides canopy area, so they can be used on images with different spatial resolution (for example: asymmetry, border index, elliptic fit, and roundness).

Acknowledgements

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Appendices

Appendix 2.1. Article disclaimer

DIVISION OF AGRICULTURE
RESEARCH & EXTENSION
University of Arkansas System

October 20, 2014

Graduate School

University of Arkansas

Fayetteville, AR 72701

As the major professor for Josue Nahun Leiva, I certify that he completed at least 51% of the work for the manuscript submitted to ‘Computers and Electronics in Agriculture’ titled ‘Effect of Flight Altitude (Spatial Resolution) and Canopy Separation on Plant Counting Accuracy Using Black Fabric and Gravel as Ground Cover’.

Sincerely,

____

James A. Robbins, Ph.D

Professor

Appendix 2.2. Example of the process used to train an algorithm using Feature Analyst®

A new feature class is created to digitize a training set. Circles are used to select 'samples' that will capture spectral and spatial variations of target plants (Fig. 2.2.1). All training samples are part of the training set.

Fig. 2.2.1. Positions of training samples.

A supervised learning was run with the following settings for each parameter:

- Feature selector: natural feature (used to extract individual trees, shrubs or other individual natural features).
- Bands: All three bands (RGB) are selected with their original resolution (no resampling)

- Input representation: manhattan

- Pattern width: 5

- Format output: vector

- Post processing: No post processing is applied in this step.

An example of the supervised learning window is provided in Fig. 2.2.2.

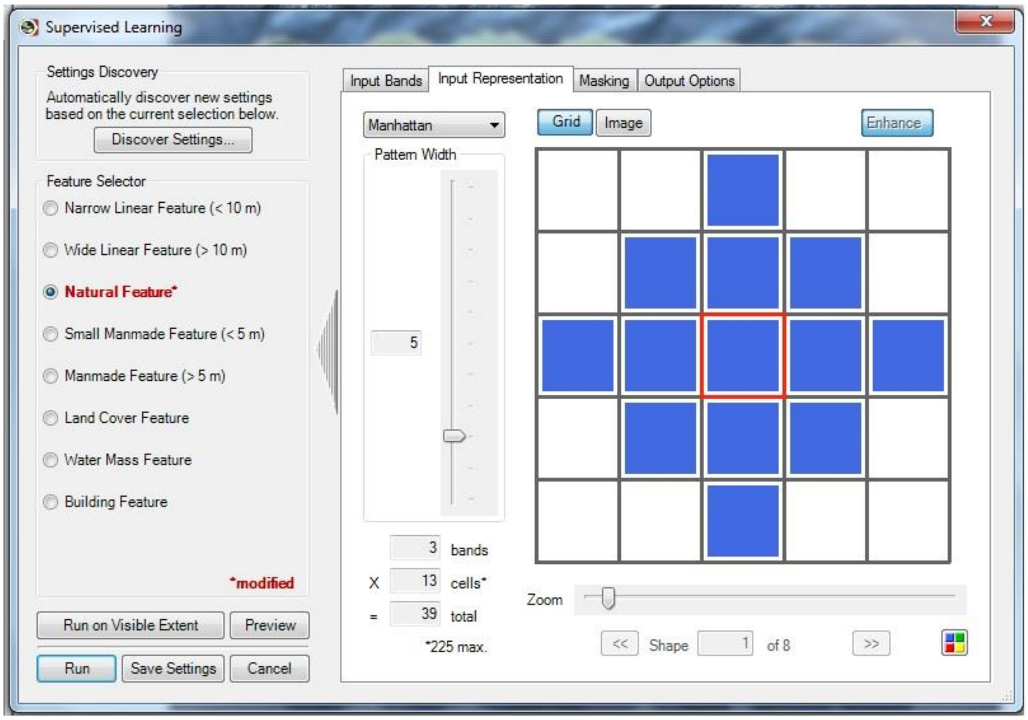

Fig. 2.2.2. Supervised learning/Input representation settings

Fig. 2.2.3. Shows the extraction executed after the learning process was applied. If the extraction does not resemble target features to be extracted or counted, this process will be repeated as many times as necessary, changing position, number and size of training samples, and/or pattern width.

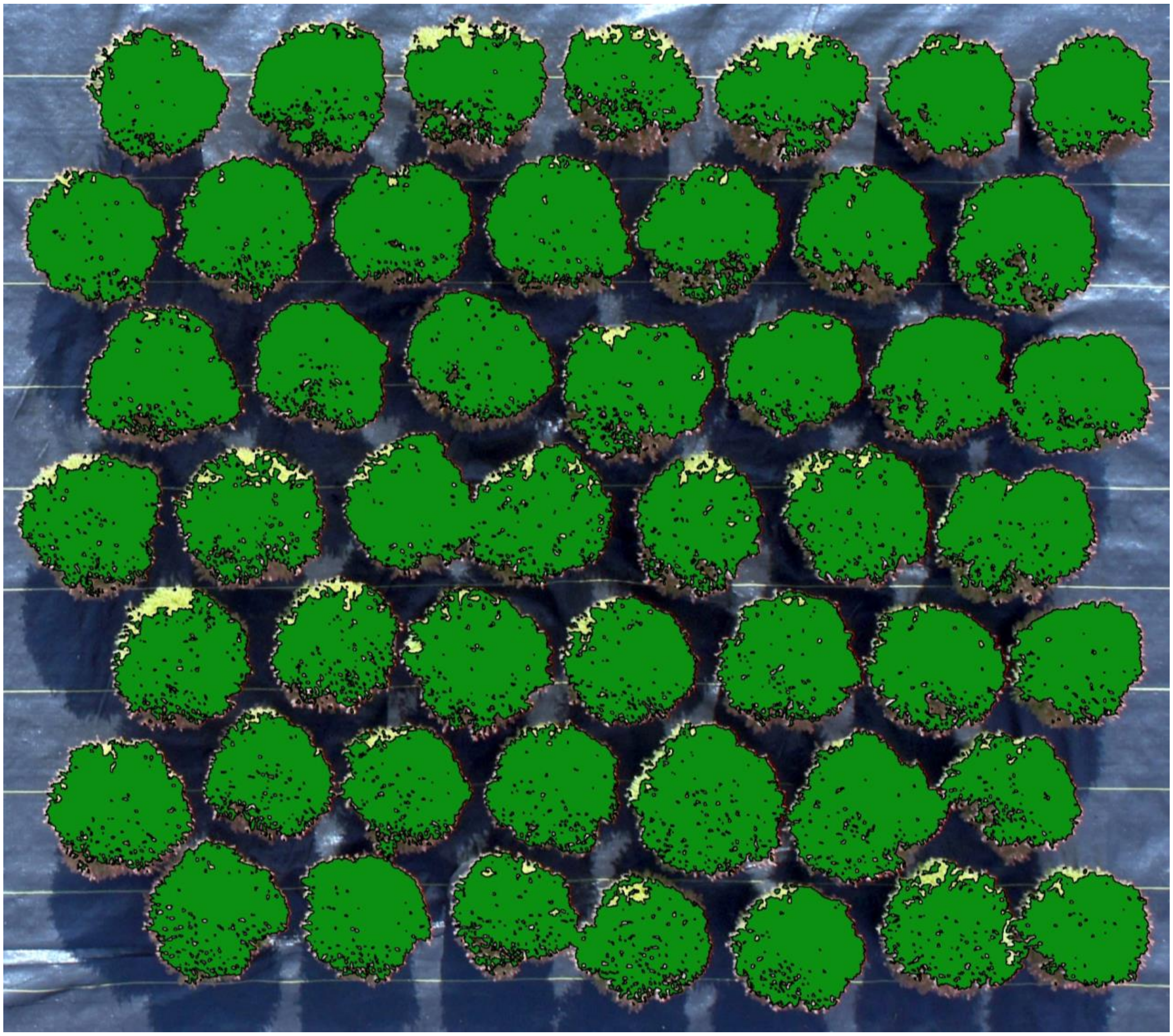

Fig. 2.2.3. Feature extraction in Feature Analyst®

Once the extraction resemble the target features, aggregation procedure is applied (Fig. 2.2.4). Aggregation allows the operator to fill holes in polygons or remove polygons that fail to meet the specified size requirement.

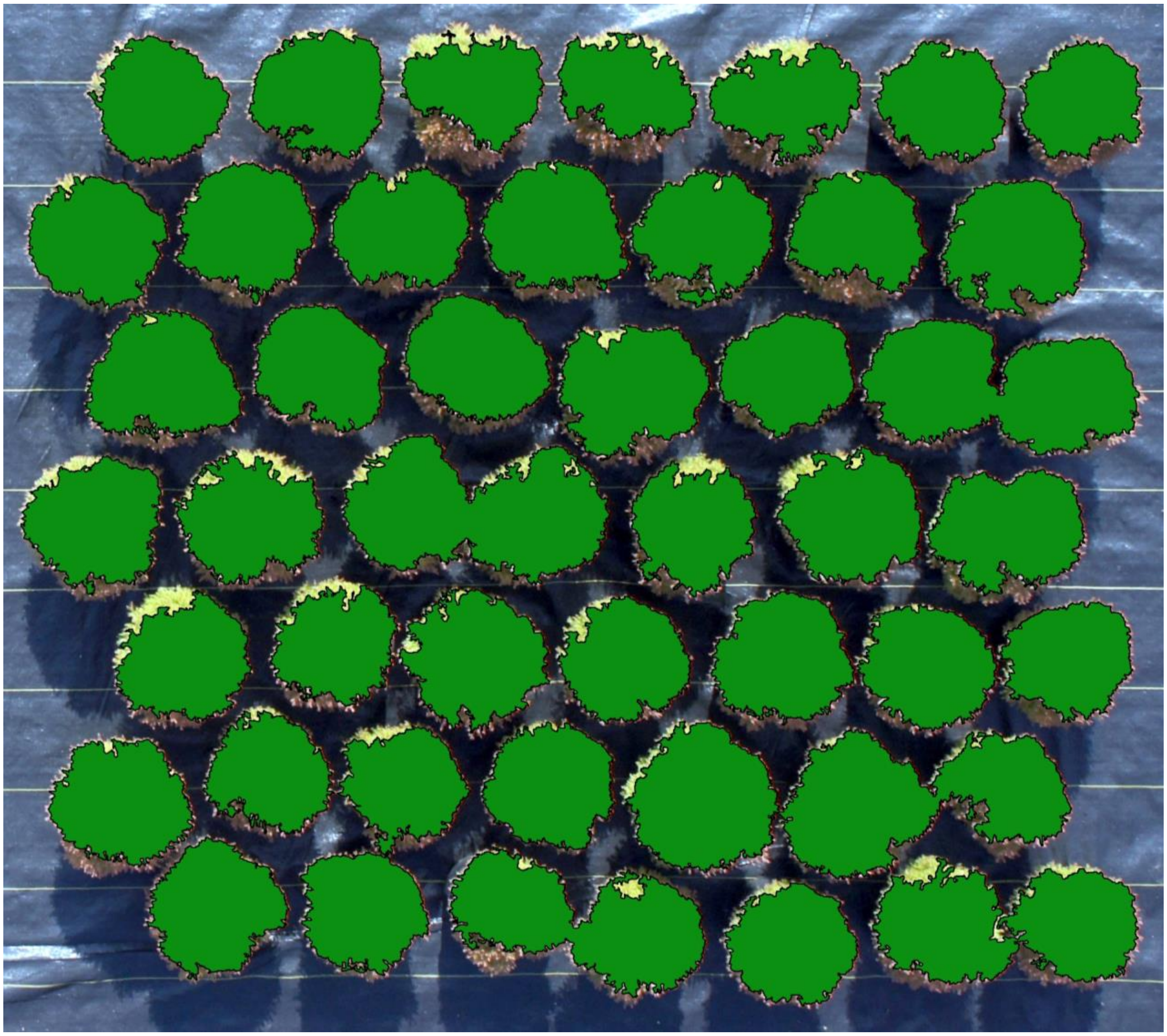

Fig. 2.2.4. Polygons after aggregation was applied. Size requirement for this image was 1450 pixels.

The next step is to apply a process call erosion. In simple terms, erosion is a method to separate target objects that are connected (Fig. 2.2.5). Since the erosion procedure can only be applied to raster formats, the ‘convert vector to raster’ tool is used before applying erosion.

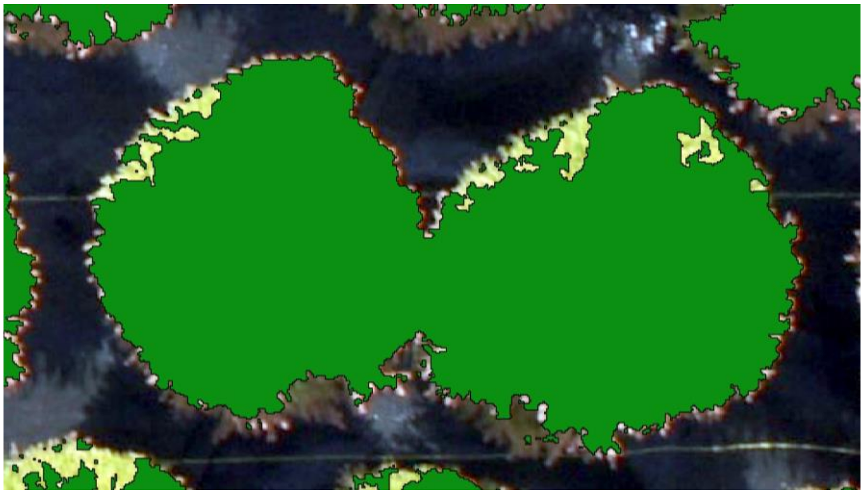

Fig. 2.2.5. Two target plants with canopies overlapping.

Figure 2.2.6 illustrates before and after erosion was applied. The erosion procedure reduces object size by determining if pixels are enclosed within an object. Size parameters used to erode polygons will depend on how much target features overlap.

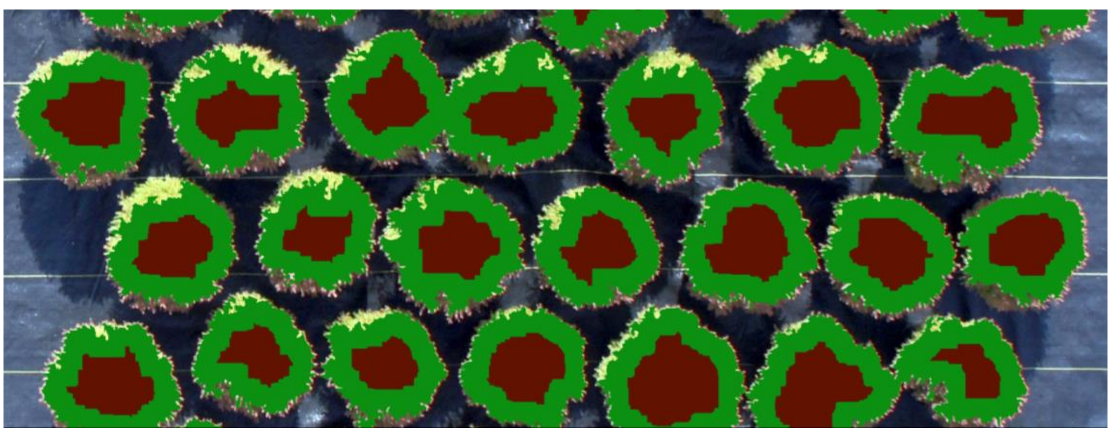

Fig. 2.2.6. Orange color are the polygons before erosion, and red ones, after erosion.

After erosion in applied, the format is changed from raster to vector (Fig. 2.2.7) because the following tools are only applicable to vector formats.

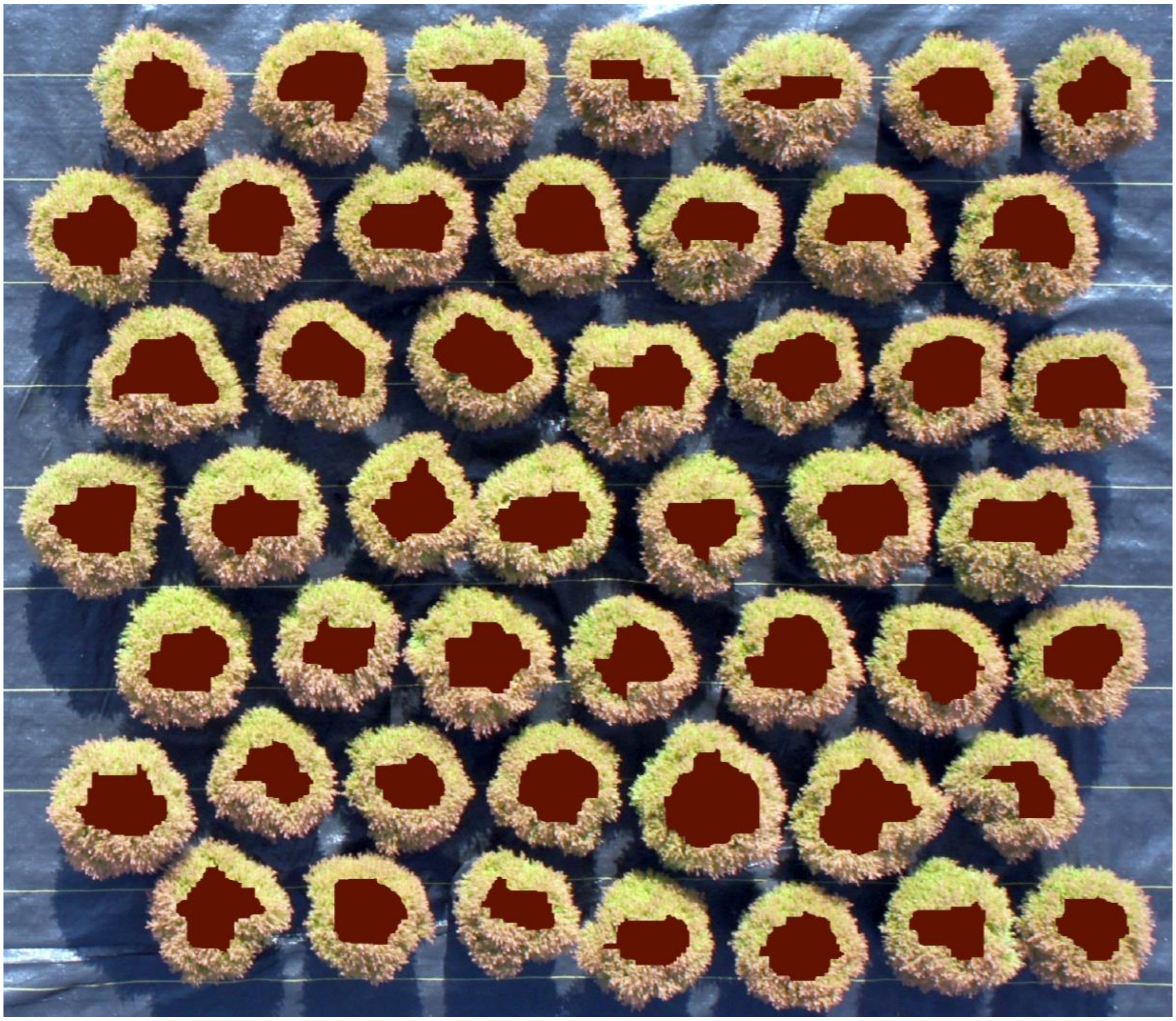

Fig. 2.2.7. Polygons converted to vector format.

Not all polygons are visible in Fig. 2.2.7. There are several polygons that cannot be seen due to their small size. For this example, only large polygons representing target plants should be kept. Polygon area is calculated using the 'create vector metrics' tool. Once areas are calculated, objects that do not meet a size requirement will be deleted, using the aggregation tool. After aggregation is applied, only 49 polygons remain in this example. In order to manually count false positives and unidentified plants, polygons are converted to points (Fig. 2.2.8)

Fig. 2.2.8. Polygons converted to large points using Feature Analyst®.

After the last procedure is applied (conversion from polygons to points), FA creates an 'automated feature extraction' (AFE) model that stores training set data and all procedures applied. The algorithm is applied to the respective treatment set images using the AFE model and the batch processing tool. The batch processing tool allows the operator to apply one AFE model to several images at the same time. A representation of the AFE model can be seen in Fig. 2.2.9.

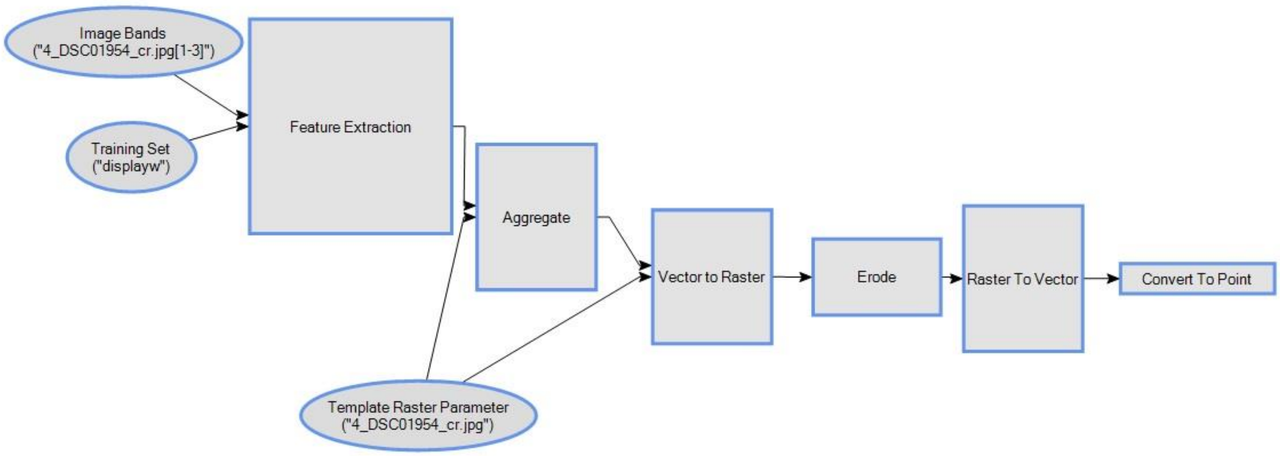

Fig. 2.2.9. Graphic representation of an <u>automated feature extraction</u> model using Feature Analyst®.

The order and times that procedures are used will change as needed to obtain the highest accuracy possible. Also, other procedures not mentioned may be used for different images.

CHAPTER THREE: EFFECT OF PLANT CANOPY SHAPE, FLOWERS, AND PLANT STATUS ON PLANT COUNT ACCURACY USING REMOTE SENSING IMAGERY

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Abstract

In general, the nursery industry lacks an automated inventory control system. Remote sensing images combined with image processing software have been used to count citrus trees, olive trees and corn plants. This technology has the potential for use in counting plants in nurseries. Separate experiments were designed to evaluate the effect of plant canopy shape, presence of flowers, and plant status (i.e. living or dead) on counting accuracy of container-grown plants. Images were taken at 12 m above the ground. Plants were placed on a black fabric in staggered rows separated 5 cm between canopy edges. Two species of juniper (*Juniperus chinensis* L. 'Sea Green' and *Juniperus horizontalis* 'Plumosa Compacta') were selected to evaluate plant shape; Coral Drift ® rose (*Rosa* sp. 'Meidrifora') was used to evaluate the presences of flowers and Buxus × 'Green Velvet' was used to evaluate plant status (living or dead plants). Count algorithms were trained using Feature Analyst (FA) and MATLAB. Total count error, false positives and unidentified plants were recorded from output images when using FA. When FA was used there was no difference between all variables measured when an algorithm trained with an image displaying regular or irregular plant canopy shape was applied to images

displaying both plant canopy shapes even though the canopy shape of ‘Sea Green’ is less compact than ‘Plumosa Compacta’. There was a significant difference in all variables measured between images of flowering and non-flowering plants when non-flowering ‘samples’ were used the train the counting algorithm in FA; total count errors and unidentified plants was greater for flowering plants. In this specific case, applying an algorithm that did not include a training set representing flowers, resulted in a less accurate count. No dead plants were counted as living and vice versa when data were analyzed using FA. When the algorithm trained in MATLAB was applied, there was no significant difference in total count errors when plant canopy shape and presence of flowers were evaluated. Based on the combined result from these separate experiments, FA and MATLAB algorithms appear to be fairly robust when used to count container-grown plants from images taken at 12 m.

Keywords:

nursery inventory, OBIA, UAV, MATLAB, Feature Analyst, canopy, roses, algorithm

Introduction

In general, the nursery industry lacks an automated inventory control system (Harkess, 2005). 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, forest tree growers often count only a portion of their crop (Hale, 1985). In the last few years some improvements have been made in the inventory process such as the adoption of computers, software (Hodges et al., 2008; USDA, 2013), and mobile personal digital assistants (Brownsberger et al., 2001). While these technologies have helped in the processing of inventory data, data are still collected manually. Other technologies such as radio frequency identification

(RFID) and bar codes are helping with the collection of inventory data but they have limitations such as the need for line-of-sight, signal transmission errors (Janam Technologies, 2011; Saraswat and Robbins, 2011), plant damage (Luvisi et al., 2010) and adaptability into large nurseries (Schuch and Klein, 1996).

Aerial images combined with image processing software have been used to identify tree species composition (Hájek, 2006), crops and vegetation monitoring (Hunt et al., 2005; Furfaro et al., 2007; Shank, 2009; Bumgarner et al., 2012; Lebourgeois et al., 2012), and land cover classification (Akasheh et al., 2008; Dunford et al., 2009; Miller et al., 2009; Tombre et al., 2010). Both technologies have been used to detect a variety of individual objects such as bats (Hamilton et al., 2009), cattle and horses (Terletzky and Ramsey, 2014), marine birds (Groom, et al., 2013), and forest tree crowns (Wulder, 1998; Wulder et al., 2000; Pitkänen, 2001; Pouliot et al., 2002; Leckie et al., 2003; Tiede et al., 2005; Bunting and Lucas, 2006). Additionally, algorithms have been developed to count citrus trees (Ayyalamayajula et al., 2009), olive trees (Karantzalos and Argialas, 2004) and corn plants (Shrestha and Steward, 2003). This technology could be used for counting plants in nurseries.

Several factors contribute to the complexity of imagery used for plant inventory analysis including plant characteristics (plant color, species, plant size and shape, canopy cover, plant health), ground/surface characteristics (bare soil, gravel, ground cloth), and environmental factors (sunlight/shadows). Because these factors could influence the analysis of data obtained from remote sensing images, these conditions must be accounted for when using these images.

Since nurseries grow a wide range of plants this may require several counting algorithms. This study was designed to evaluate the effect of plant canopy shape, presence of flowers, and plant status (living or dead) on counting accuracy of container-grown plants.

Materials and Methods

For this, and subsequent studies, the plan was to continue using the UAV to obtain remote sensing images, however, some UAV users worldwide that rely on GPS-based navigation faced an unexpected problem in 2013 (Siegfried, 2013). Solar flares follow an approximate 11-year cycle (Hathaway, 2014). One such peak occurred in the fall of 2013 making 'as needed' flights using automated features of the Mikrokopter difficult. A log of X-ray and magnetic field activity is presented in Appendix 3.1. For example, during a 170 day period (November 30th to May 19th, 2013), X-ray activity was ‘normal’ on only 6 days. Based on discussions in a user forum (http://forum.mikrokopter.de), we were advised (J. Maja, personal communication, 27 March, 2013) to fly the Mikrokopter only on days when the solar X-ray and geomagnetic field activity were ‘normal’ and 'quiet', respectively, as reported by NOAA (http://www.n3kl.org/sun/noaa.html), however, these personal advisories are not scientifically validated. Although current X-ray and geomagnetic field activity are reported daily, these activities cannot be forecast making it difficult to schedule future flights. While solar flare activity has long been known to disrupt GPS and other communications signals (Ya’acob et al., 2013), it was never anticipated to be a problem when most of the UAVs were originally designed by engineers.

The canopy shape experiment was set-up on October 22, 2013 but due to 'active' solar flare activity we could not conduct a UAV flight until November 11. Even though the solar flare activity was still 'active' on that date, we attempted to fly using GPS navigation with the result of the UAV crashing. The manufacturer provided a possible solution to the solar flare interference problem in late May 2014, however, this hardware upgrade has not yet been tested. As a result of these unexpected issues we decided to use a boom lift that could provide necessary images on a more reliable basis. A locally available lift boom that could reach 12 m was used for the following experiments.

Canopy shape

Sensor

A Sony Alpha NEX-7 (Sony Corporation of America IR, San Diego, CA), 24.3 megapixels color digital frame camera, with an 18-55 mm lens was used as the sensor. The shooting mode was set as manual with an ISO of 200, shutter speed of 1/250 seconds, f value of 8 and 4 bits/pixel. Autofocusing and aspect ratio of 3:2 were fixed. Flash, object tracking, and face detection were turned off. Images from this sensor contain three bands: red, green and blue.

Experimental design

Container-grown plants were spaced in staggered rows with a canopy separation of 5 cm between canopy edges. Two species of juniper (*Juniperus chinensis* L. ‘Sea Green’ and *Juniperus horizontalis* Moench ‘Plumosa Compacta’) growing in #2 black polyethylene containers (height: 21.6 cm, top diameter: 22.9 cm, and bottom diameter: 19.7 cm) (Plastics Inc., Jacksonville, TX) were used in the study since they were available in large numbers and the foliage, texture, and color was similar (Fig. 3.1). Henceforth, the canopy for ‘Plumosa Compacta’ will be referred as ‘regular’ and ‘Sea Green’ canopy as ‘irregular’. For each canopy shape treatment, a set of 64 containers (8 × 8) was established outdoors on black polypropylene fabric ground cover (Lumite, Inc., Alto, GA) on 13 November, 2013 at Greenleaf Nursery, Park Hill, OK (35.779098, -94.904323). Treatment sets were replicated five times in a randomized complete block design (RCBD) for a total of 10 sets. Six sets of four fully separated plants were positioned between treatment sets and were used to train an algorithm using MATLAB® (MathWorks Inc., Natick, MA) (MATLAB). Three of these training sets contained plants with a regular canopy shape and the remaining contained plants with an irregular canopy shape (Fig. 3.2). Two additional sets of 49 containers (7 × 7), one with 'Sea Green' juniper and the other with 'Plumosa Compacta', were positioned adjacent to the treatment sets and were used to train the algorithm using FA, and henceforth referred to as training sets (Fig. 3.2). The number of plants used in training and treatment sets was determined based on criteria previously described. Four plants per set were used for plant measurements. These were the corner plants on each set. Shoot height was measured from the substrate surface to the top of the plant. Average shoot height was 40 and 27 cm for 'Sea Green' and 'Plumosa Compacta' junipers, respectively. Average shoot diameter was determined by taking two measurements at 90^{o} from each other. Average shoot diameter was 49 and 39 cm for 'Sea Green' and 'Plumosa Compacta', respectively. RGB mean values were calculated from an aerial image at 0.15 cm/pixel spatial resolution, under sunny conditions using eCognition (Trimble©, Westminster, CO) for plant canopy and ground covers resulting in 81±51, 84±50, 53±43 for 'Plumosa Compacta', 60±45, 72±47, 41±36 for 'Sea Green', and 15±17, 20±16, 31±14 for the black fabric. The image was taken using the same camera used for all images with an f value = 8, shutter speed= 1/250 seconds. Other settings were the same as previously described.

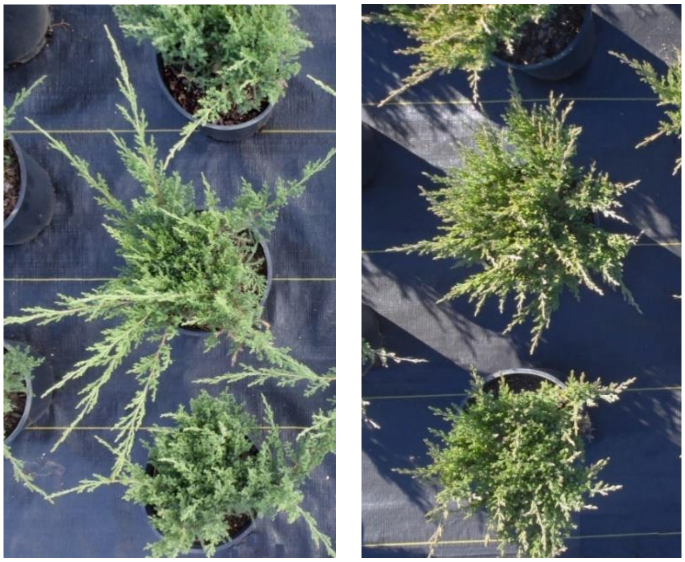
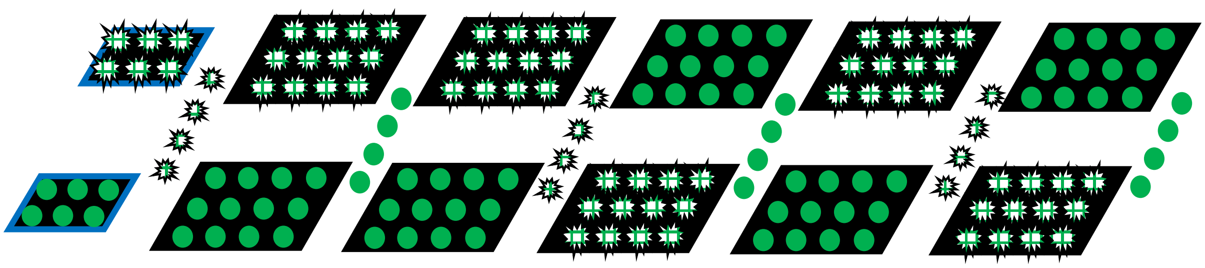


Fig. 3.1. Two species of juniper, left: *Juniperus chinensis* L. 'Sea Green' (irregular shape), right: *Juniperus horizontalis* 'Plumosa Compacta' (regular shape).



Regular canopy shape

Irregular canopy shape

Fig. 3.2. Illustration of the experimental design. Training sets used in Feature Analyst® are the two smaller sets on the left, the remainder are treatment sets. The four plants positioned outside black squares represent plants used to train the algorithm written in MATLAB®.

Data collection

Images were obtained by extending a Bil-Jax 3632T boom lift (Haulotte Group, Archbold, OH) to 12 m above ground level. To obtain images centered over blocks required moving the boom lift. Each time the boom was re-positioned, sensor height relative to the ground was determined using a measuring tape. The sensor, which was handheld, was positioned over the center of every block, resulting in both sets for that block being included in the image. Image spatial resolution was calculated based on 20 cm square white boards positioned around the treatment blocks, resulting in 0.15 cm/pixel. Two images of each set were taken and then used for algorithm evaluation.

Variables

When FA was used, 3 variables were measured using the final count and output image as follows:

Total count error: total software count – ground count. Total count error is also presented as percentages based on the ground count from the set.

False positives: counts that do not represent a target plant (e.g. multiple counts, weeds or other objects within the ground cover that were counted as a plant).

Unidentified: target plants that were not counted.

The algorithm trained using MATLAB does not generate an output image, therefore, only total count error is reported. Means were separated using an analysis of variance followed by a Student’s t-test based on the experimental design described above using SAS 9.3 (SAS Institute Inc., Cary, NC). No statistical comparison was made between results obtained using the two software packages.

Environmental parameters

Environmental parameters including light intensity (140 LUX), relative humidity (24.4%), temperature (15.6° C), and ground wind speed (0-4 km/h) were measured using a Mini Environmental Quality Meter (Sper Scientific, Scottsdale, AZ) before images were collected (1020). A subjective estimate of cloud cover was determined to be less than 5%.

Image selection

One image per set was selected using the following criterion:

- The experimental unit must be completely displayed within the images.
- Priority was given to images with the most centered treatment set.

In order to decrease image processing time, images were cropped and rotated using Adobe Photoshop Elements 6 (Adobe System Incorporated, San Jose, CA) leaving only the set of interest for that particular image.

Algorithm training using Feature Analyst® (FA)

A total of two algorithms were trained, one for each canopy shape. Each algorithm was applied to all images regardless of canopy shape. The general process of training an algorithm was as described in the previous chapter.

Algorithm training using MATLAB

A counting algorithm was written using MATLAB (R2013b). Procedures described in the previous chapter were used to train this algorithm, with the exception that a different ratio was used to extract plants from the ground: 2*G-B-R.

Presence of flowers

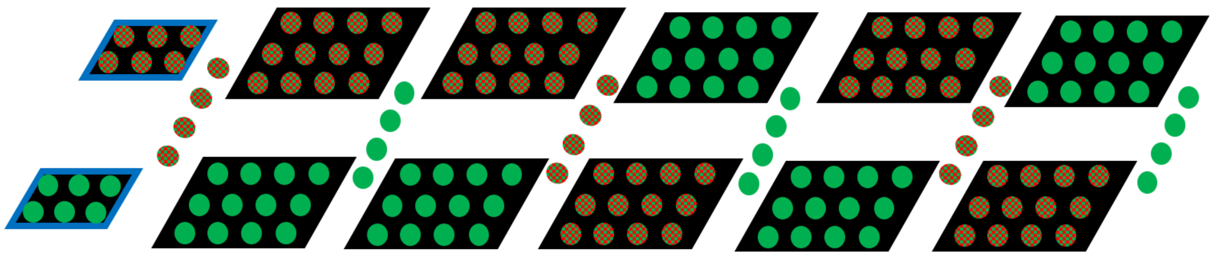
Sensor

A Sony Alpha NEX-7 (Sony Corporation of America IR, San Diego, CA), 24.3 megapixels color digital frame camera, with an 18-55 mm lens was used as the sensor. The shooting mode was set as manual with an ISO of 200, shutter speed of 1/250 seconds, f value of 8 and 4 bits/pixel. Autofocusing and aspect ratio of 3:2 were fixed. Flash, object tracking, and face detection were turned off.

Experimental design

Container-grown plants were spaced in staggered rows with a canopy separation of 5 cm between canopy edges. Coral Drift® rose (*Rosa* sp. 'Meidrifora') growing in true #1 yellow/green polyethylene containers (height: 17.8 cm, top diameter: 19.7 cm, and bottom diameter: 15.9 cm) (Nurseries Supplies Inc., Chambersburg, PA) were used in the study since they were available in large numbers. Plants were pulled from nursery production blocks. Two treatments were evaluated: 1) roses with coral flowers and 2) roses without flowers; for the latter, flowers were removed manually (Fig. 3.3). For each treatment, a set of 64 containers (8 × 8) was established outdoors on black polypropylene fabric ground cover on 13 November, 2013 at Greenleaf Nursery, Park Hill, OK (35.779098, -94.904323). Treatment sets were replicated five times in a randomized complete block design (RCBD) for a total of 10 sets. Two images of each set were taken and then used for algorithm evaluation. Six sets of four fully separated plants were positioned between treatment sets and were used to train an algorithm using MATLAB; three of these sets contained plants with flowers and the remainder contained plants without flowers (Fig. 3.4). Two additional sets of 49 containers (7 × 7), one containing plants with flowers and the other without flowers were positioned adjacent to the treatment sets and were used to train the FA algorithm, and henceforth, referred to as training sets (Fig. 3.4). The number of plants used in training and treatment sets was determined based on criteria previously described. Four corner plants per set were used for plant measurements. Shoot height was measured from the substrate surface to the top of the plant. Average shoot height was 25 cm. Average shoot diameter was determined by taking two measurements at 90^o from each other. Average shoot diameter was 30 cm. RGB mean values were calculated from an aerial image at 0.15 cm/pixel spatial resolution, under sunny conditions using eCognition for plant canopy and ground covers resulting in 139±62, 115±55, 99±55 for roses with flowers, 131±53, 122±52, 98±51 for roses without flowers, and 125±43, 128±42, 139±39 for the black fabric. The image used to calculate RGB mean values was taken using the same camera used for all images with an f value = 8, shutter speed= 1/250 seconds. Other settings were the same as previously described.

Fig. 3.3. Coral Drift ® rose plant with flowers (left) and without flowers (right).



● Non-flowering plant

● Flowering plant

Fig. 3.4. Illustration of the experimental design. Training sets used in Feature Analyst® are the two smaller sets on the left, the remainder are treatment sets. Plants positioned outside black squares were used to train the algorithm written in MATLAB®.

Data collection, variables measured and image selection parameters are the same as those described in the canopy shape experiment.

Environmental parameters

Environmental parameters including light intensity (140 LUX), relative humidity (24.4%), temperature (15.6° C), and ground wind speed (0-4 km/h) were measured using a Mini Environmental Quality Meter at the beginning of image collection (1300). A subjective estimate of cloud cover was determined to be less than 5%.

Algorithm training

Algorithm training procedures using FA were similar to those described in the canopy shape experiment. A total of two algorithms were trained, one for plants with flowers and another for plants without them. Each algorithm was applied to all images regardless of presence of flowers. A counting algorithm was written using MATLAB as described in the previous chapter, with the exception that a different ratio was used to extract plants from the ground cover: G+R-2*B.

Plant status (living or dead)

Sensor

A Sony Alpha NEX-7 was used as the sensor. The shooting mode was set as manual with an ISO of 200, shutter speed of 1/320 seconds, f value of 9, and 3 bits/pixel. Autofocusing and aspect ratio of 3:2 were fixed. Flash, object tracking, and face detection were turned off.

Experimental design

Container-grown plants were spaced in staggered rows with a canopy separation of 5 cm between canopy edges. Buxus × 'Green Velvet' growing in #2 black polyethylene containers (height: 21.6 cm, top diameter: 22.9 cm, and bottom diameter: 19.7 cm) (Plastics Inc., Jacksonville, TX) were used in the study since they were available in large numbers. Living and dead boxwood plants were selected from production blocks. The dead plants still retained a majority of brown leaves (Fig. 3.5). For each treatment, a set of 49 containers (7 × 7) were established outdoors on black polypropylene fabric ground cover on 16 May, 2014 at Greenleaf Nursery, Park Hill, OK (35.779098, -94.904323). Treatments consisted of sets with only living plants, and sets with 14% dead plants randomly positioned within the set (Fig. 3.6). Treatment sets were replicated four times in a randomized complete block design (RCBD) for a total of 8 sets. Two additional sets representing both treatments, were positioned adjacent to the treatment sets and were used to train the algorithm using FA, and henceforth referred to as training sets. After taking images from all sets at 1010, a second round of images were taken at 1245. Two images of each set were taken at 12 m above the ground (one per each round) and then used for algorithm evaluation. Four plants per set were used for plant measurements. These were the corner plants on each set. Shoot height was measured from the substrate surface to the top of the plant. Average shoot height was 38 and 36 cm for living and dead plants, respectively. Average shoot diameter was determined by taking two measurements at 90º from each other. Average shoot diameter was 35 and 29 cm for living and dead plants, respectively. RGB mean values were calculated from an aerial image at 0.15 cm/pixel spatial resolution, under sunny conditions using eCognition (Trimble©, Westminster, CO) for plant canopy and ground cover resulting in 125±45, 149±47, 72±40 for living plants, 133±50, 96±42, 57±36 for dead plants, and 110±57, 113±56, 118±56 for the black fabric. The image was taken using the same camera and settings used for all images. Other settings were the same as previously described.

Fig. 3.5. Photograph of a dead Buxus × 'Green Velvet' with its leaves still retained in a treatment set.

Fig. 3.6. Left: set with 0% dead plants. Right: set with 14% dead plants.

Algorithm training

Algorithm training procedures using FA were similar to those described in the previous chapter, with the exception that when using a training image with 14% dead plants, all dead plants (7) were used when digitizing training samples. A total of two algorithms were trained, one for living plants and the other for dead plants. Each algorithm was applied to all images. Dead plants identified as alive, and vice versa, were calculated using output images from the algorithm. Images were not analyzed using the algorithm trained in MATLAB due to time restrictions of the graduate student at the University of Florida.

Variables

In order to determine if the algorithm could distinguish between dead and living plants, the number of living plants counted as dead was recorded when the algorithm was trained using dead plants and, the number of plants counted as living was recorded when the algorithm was trained using an image containing only living plants. Since the number of living plants is different in both treatment sets, count accuracy data are not comparable. Image selection parameters are the same as those described in the previous chapter.

Environmental parameters

Environmental parameters including light intensity (146 LUX), relative humidity (24.9%), temperature (33.4° C), and ground wind speed (0-5 km/h) were measured using a Mini Environmental Quality Meter (Sper Scientific, Scottsdale, AZ) before image collection. A subjective estimate of cloud cover was determined to be less than 5%.

Results and discussion

Canopy shape

Algorithm trained using images displaying plants with regular canopy shape

An algorithm was trained using a training image displaying junipers with a regular canopy shape using FA and then applied to images displaying junipers with regular and irregular canopy shapes. There were no significant differences between canopy shape treatments for total count error ($F=0.30$, $p=0.6013$), false positives ($F=2.25$, $p=0.1679$), and unidentified plants ($F=0.54$, $p=0.4817$) when the data were analyzed using FA (Table 3.1). In contrast to experiments conducted using a UAV (Chapter two), the distance of the camera to the ground was more consistent, resulting in higher count accuracy due to a more consistent spatial resolution between images. Since the canopy shape was irregular, it is possible that some branches overlapped causing minor conflicts for the algorithm to resolve, resulting in small count errors (two or more plants counted as one, generating unidentified plants). When data were analyzed with the algorithm trained using MATLAB, there was no significant difference between total count errors for both canopy shape treatments ($F=4.94$, $p=0.0506$) (Table 3.2).

Table 3.1. Count accuracy for container-grown junipers with regular (*Juniperus horizontalis* 'Plumosa Compacta') and irregular (*Juniperus chinensis* L. 'Sea Green') canopy shapes when training an algorithm with images displaying junipers with regular canopy shape using Feature Analyst®

Canopy shape	Total count error		False positives		Unidentified plants	
	No.[z]	%[y]	No.[x]	%	No.	%
Regular	-2	-3%	0	0%	2	3%
Irregular	-1	-2%	0	0%	1	2%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64.
[y]Total count error, false positive, and unidentified plants expressed as percentages; total count error/ground count × 100.
[x]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant).

Table 3.2. Count accuracy for container-grown junipers with regular (*Juniperus horizontalis* 'Plumosa Compacta') and irregular (*Juniperus chinensis* L. 'Sea Green') canopy shapes when training an algorithm with images displaying junipers with regular canopy shape using MATLAB®

Canopy shape	Total count error	
	No.[z]	%[y]
Regular	0	0%
Irregular	3	2%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64.
[y]Total count error, false positive, and unidentified plants expressed as percentages; total count error/ground count × 100.

Algorithm trained using images displaying plants with irregular canopy shape

An algorithm was trained using a training image displaying junipers with an irregular canopy shape and then applied to images displaying junipers with regular and irregular canopy shapes. There were no significant differences between canopy shape treatments for total count error (F=0.12, p=0.7337), false positives (F=3.27, p=0.0872), and unidentified plants (F=0.01, p=0.9165) when data were analyzed using FA (Table 3.3). When images were analyzed with the algorithm trained in MATLAB, total count error did not show a significant difference ($F=4.61$, $p=0.0574$) between canopy shape treatments (Table 3.4). Regardless of whether a plant with a regular canopy shape or an irregular is used to train the algorithm in MATLAB, results are similar.

Table 3.3. Count accuracy for container-grown junipers with regular (*Juniperus horizontalis* 'Plumosa Compacta') and irregular (*Juniperus chinensis* L. 'Sea Green') canopy shape when training an algorithm with images displaying junipers with irregular canopy shape using Feature Analyst®

Canopy shape	Total count error		False positives		Unidentified plants	
	No.[z]	%[y]	No.[x]	%	No.	%
Regular	-1	-2%	0	0%	1	2%
Irregular	-1	-2%	0	0%	1	2%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64.
[y]Total count error, false positive and unidentified plants expressed as percentages; total count error/ground count × 100.
[x]False positives: counts that do not represent a plant (e.g. multiple counts, weeds or other objects within the ground cover that were count as a plant).

Table 3.4. Count accuracy for container-grown junipers with regular (*Juniperus horizontalis* 'Plumosa Compacta') and irregular (*Juniperus chinensis* L. 'Sea Green') canopy shapes when training an algorithm with images displaying junipers with irregular canopy shape using MATLAB®

Canopy shape	Total count error	
	No.[z]	%[y]
Regular	-2	-3%
Irregular	1	2%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64.
[y]Total count error, false positive, and unidentified plants expressed as percentages; total count error/ground count × 100.

When data were analyzed with FA and the MATLAB algorithm, there was no difference between variables measured when an algorithm trained with an image displaying regular or irregular plant canopy shape was applied to images displaying either of the plant canopy shapes. Even though the canopy shape of ‘Sea Green’ is less compact than ‘Plumosa Compacta’, visible individual lateral branches are eliminated when applying the erosion procedure, thus making FA algorithms performances similarly. The erosion procedure reduces object size by determining if pixels are enclosed within an object (Richards, 2012). Since the MATLAB algorithm is based on area derived from training plants, results might be explained by a similar area between both juniper cultivars, regardless of their shape.

When using FA, one set of training samples was selected by the user from one training image and then the training set was used to analyze different images. Since different users would likely pick different training sets, expectations were that this user input was going to increase experimental error, however, if there is an effect related to this process, it appears to have a minimal effect on count accuracy for juniper plants.

Presence of flowers

Algorithm trained using images displaying plants with flowers

An algorithm was trained using an image displaying plants with flowers and then applied to images displaying plants with and without them. Total count error (F=0.60, p=0.4617), false positives (F=0.00, p=1.00), and unidentified plants (F=0.60, 0.4617) means generated with FA (Table 3.5), and total count error with an algorithm written using MATLAB (F=1.5, p=0.2596) (Table 3.6), indicate no significant differences for flowering and non-flowering treatments.

Table 3.5. Count accuracy for container-grown Coral Drift ® rose (*Rosa* sp. 'Meidrifora') with and without flowers placed on a black fabric ground cover, when training an algorithm with images displaying flowering roses using Feature Analyst®

Treatment sets	Total count error		False positives		Unidentified	
	No.[z]	%[y]	No.	%	No.	%
Flowering	-1	-2%	1	2%	2	3%
Non-flowering	-2	-3%	1	2%	3	5%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64.
[y]Variables expressed as percentages; variable/ground count × 100.

Table 3.6. Count accuracy for container-grown Coral Drift ® rose (*Rosa* sp. 'Meidrifora') with and without flowers placed on a black fabric ground cover, when training an algorithm with images displaying flowering roses using MATLAB®

Treatment	Total count error	
	No.[z]	%[y]
Flowering roses	-1	-2%
Non-flowering roses	-3	5%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64.
[y]Variables expressed as percentages; variable/ground count × 100.

When training samples were digitized using plants with flowers in FA, pixels from leaves/stems and flowers were included. This approach works well to extract plants without flowers since the sample included pixels representing leaves. Count accuracy may also be high since there were small differences in RGB mean values between treatments (139±62, 115±55, 99±55 for roses with flowers, 131±53, 122±52, 98±51 for roses without flowers).

Algorithm trained using images displaying plants without flowers

FA was trained using an image displaying plants without flowers and then applied to images displaying plants with and without flowers. There was a significant difference in total count error (F=11.54, p=0.0274), false positives (F=4.85, p=0.0450) and unidentified plants (F=8.94, p=0.0403) between images of flowering and non-flowering plants when images were analyzed with FA (Table 3.7). When expressed as percentages, total count errors and unidentified plants were greater for flowering plants. This may be explained by the lack of a representative training set that excludes pixels representing coral flowers, resulting in a less consistent extraction. Even though RGB mean values between plants with and without flowers were fairly similar, FA may require a more representative training sample for this case. When the same data were analyzed with the algorithm trained in MATLAB there was no significant difference (F=0.07, 0=0.8055) between flowering and non-flowering treatments (Table 3.8). The algorithm trained in MATLAB may have yielded better counting results because the index used to extract the plants creates a better segmentation than the one executed by the learning process used in FA. Since MATLAB relies on canopy area, its performance is not affected by the removal of flowers because that does not change the overall canopy area.

Table 3.7. Total count accuracy for container-grown Coral Drift ® rose (*Rosa* sp. 'Meidrifora') with and without flowers placed on a black fabric ground cover, when training an algorithm with images displaying non-flowering roses using Feature Analyst®

Treatment	Total count error		False positives		Unidentified	
	No.[z]	%[y]	No.	%	No.	%
Flowering	-6 a[x]	-9%	1 a	2%	7 a	11%
Non-flowering	0 b	-0%	2 b	3%	2 b	3%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64.
[y]Variables expressed as percentages; variable/ground count × 100.
[x]Means followed by the same letter within the same column are not significantly different based on a Student's t-test (p≤0.05).

Table 3.8. Count accuracy for container-grown Coral Drift ® rose (*Rosa* sp. 'Meidrifora') with and without flowers placed on a black fabric ground cover, when training an algorithm with images displaying non-flowering roses using MATLAB®

Treatment	Total count error	
	No.[z]	%[y]
Flowering roses	-2	-3%
Non-flowering roses	-2	-3%

[z]Total count error: total software count – ground count. Total count errors are based on a ground count of 64.
[y]Variables expressed as percentages; variable/ground count × 100.

Plant status (living and dead)

Algorithm trained using living plants

Since the number of living plants is different in both treatment sets, total count error, false positives and unidentified plants data are not comparable. An algorithm was trained with living plants using FA and then applied to images displaying plant sets with and without dead plants. Table 3.9 shows the number of dead plants counted as living. No dead plants were counted as living, regardless if sets contained only living plants or 14% dead plants.

Table 3.9. Number of dead Buxus x 'Green Velvet' plants counted as living when training an algorithm with living plants using Feature Analyst®

Treatment sets (% dead plants)	Number of dead plants counted as living
0%	0
14%	0

Algorithm trained using dead plants

An algorithm was trained with dead plants using FA and then applied to images displaying sets with and without dead plants. Table 3.10 shows the number of living plants counted as dead. No living plants were counted as dead regardless of the treatment set.

Table 3.10. Number of living Buxus x 'Green Velvet' plants counted as dead when training an algorithm with dead plants using Feature Analyst®

Treatment sets (%dead plants)	Number of living plants counted as dead
0%	0
14%	0

When training 'samples' are digitized containing dead or living plants, the segmentation in FA distinguished between pixel information from both classes. Haara and Nevailanen (2002) encountered difficulties when classifying dead forest trees, stating error sources as training data quality and spatial and radiometric aggregation. However, the 'Green Velvet' images used in this experiment had a consistent spatial resolution and results indicated that the training 'sample' used was representative enough that no misclassification was observed.

As discussed earlier, although all images were taken during a single day and there were minimal differences in light intensity (e.g. full sun, cloudy) between training and treatment sets, this experimental design is consistent with the focus of this study which was to evaluate the performance of algorithms within certain conditions. Justification and limitations to this approach are discussed in the previous chapter.

Conclusions

Based on the combined result from these separate experiments, FA and the algorithm trained using MATLAB looks to be fairly robust. With the exception of the algorithm trained using non-flowering roses, results from data analyzed using FA were not influenced by plant canopy shape, plant status and presence of flowers when images were taken at 12 m above ground. The algorithm trained in MATLAB did not find any differences when plant canopy shape and presence of flower were evaluated.

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Appendices

Appendix 3.1. Article disclaimer

DIVISION OF AGRICULTURE
RESEARCH & EXTENSION
University of Arkansas System

October 20, 2014

Graduate School

University of Arkansas

Fayetteville, AR 72701

As the major professor for Josue Nahun Leiva, I certify that he completed at least 51% of the work for the manuscript in chapter three, titled 'Effect of Plant Canopy Shape, Flowers, and Plant Status on Plant Count Accuracy Using Aerial Imagery'.

Sincerely,

James A. Robbins, Ph.D

Professor

Appendix 3.2. X-ray and Geomagnetic field status from November 30, 2013 to May 19, 2013.

(Data collected between 9 and 10 am)

Legend:

Geomagnetic field:

Class	Index
quiet	0 - 7
unsettled	8 - 15
active	16 - 29
minor storm	30 - 49
major storm	50 - 99
severe storm	100 - 400

X-rays:

Class ($W\ m^{-2}$)	
B	$I < 10^{-6}$ (Normal’)
C	$10^{-6} <= I < 10^{-5}$ (‘Active’)
M	$10^{-5} <= I < 10^{-4}$
X	$I >= 10^{-4}$

Date	X-Rays	Geomagnetic field
30-Nov	Normal	Unsettled
1-Dec	Active	Unsettled
2-Dec	Active	Quiet
3-Dec	Active	Quiet
4-Dec	Active	Quiet
5-Dec	Active	Quiet
6-Dec	Active	Quiet
7-Dec	M-Class flare	Quiet
8-Dec	Active	Storm
9-Dec	Active	Unsettled
10-Dec	Active	Quiet
11-Dec	Active	Quiet
12-Dec	Active	Quiet
13-Dec	Active	Quiet
14-Dec	Active	Unsettled
15-Dec	Active	Quiet
16-Dec	Active	Quiet
17-Dec	Active	Quiet
18-Dec	Active	Quiet
19-Dec	Active	Quiet
20-Dec	M-Class flare	Quiet
21-Dec	Active	Quiet
22-Dec	M-Class flare	Quiet
23-Dec	M-Class flare	Quiet
24-Dec	Active	Quiet
25-Dec	Active	Quiet
26-Dec	Active	Quiet
27-Dec	Active	Quiet
28-Dec	Active	Quiet
29-Dec	M-Class flare	Quiet
30-Dec	Active	Quiet
31-Dec	Active	Quiet
1-Jan	M-Class flare	Quiet
2-Jan	Active	Storm
3-Jan	Active	Storm
4-Jan	Active	Quiet

Date	X-Rays	Geomagnetic field
5-Jan	M-Class flare	Quiet
6-Jan	Active	Quiet
7-Jan	M-Class flare	Quiet
8-Jan	M-Class flare	Quiet
9-Jan	Active	Quiet
10-Jan	Active	Quiet
11-Jan	Active	Quiet
12-Jan	Active	Quiet
13-Jan	Active	Unsettled
14-Jan	Active	Unsettled
15-Jan	Active	Quiet
16-Jan	Active	Quiet
17-Jan	Active	Quiet
18-Jan	Active	Quiet
19-Jan	Active	Quiet
20-Jan	Active	Quiet
21-Jan	Active	Quiet
22-Jan	Active	Quiet
23-Jan	Active	Quiet
24-Jan	Active	Quiet
25-Jan	Active	Quiet
26-Jan	M-Class flare	Quiet
27-Jan	M-Class flare	Quiet
28-Jan	M-Class flare	Quiet
29-Jan	M-Class flare	Quiet
30-Jan	M-Class flare	Quiet
31-Jan	M-Class flare	Quiet
1-Feb	M-Class flare	Quiet
2-Feb	M-Class flare	Quiet
3-Feb	M-Class flare	Quiet
4-Feb	M-Class flare	Quiet
5-Feb	M-Class flare	Quiet
6-Feb	M-Class flare	Quiet
7-Feb	M-Class flare	Quiet
8-Feb	Active	Unsettled
9-Feb	M-Class flare	Storm

Date	X-Rays	Geomagnetic field
10-Feb	Active	Unsettled
11-Feb	M-Class flare	Unsettled
12-Feb	M-Class flare	Quiet
13-Feb	M-Class flare	Quiet
14-Feb	M-Class flare	Quiet
15-Feb	Active	Quiet
16-Feb	Active	Storm
17-Feb	Active	Unsettled
18-Feb	Active	Quiet
19-Feb	Active	Storm
20-Feb	Active	Storm
21-Feb	Active	Storm
22-Feb	Active	Unsettled
23-Feb	Website offline	
24-Feb	M-Class flare	Unsettled
25-Feb	X-Class flare	Quiet
26-Feb	M-Class flare	Quiet
27-Feb	Active	Quiet
28-Feb	Active	Storm
1-Mar	M-Class flare	Storm
2-Mar	Active	Quiet
3-Mar	Active	Quiet
4-Mar	Active	Quiet
5-Mar	Active	Quiet
6-Mar	Active	Quiet
7-Mar	Active	Quiet
8-Mar	Active	Quiet
9-Mar	M-Class flare	Quiet
10-Mar	M-Class flare	Quiet
11-Mar	M-Class flare	Quiet
12-Mar	M-Class flare	Quiet
13-Mar	M-Class flare	Storm
14-Mar	M-Class flare	Storm
15-Mar	Active	Quiet
16-Mar	Active	Quiet
17-Mar	Active	Quiet

Date	X-Rays	Geomagnetic field
18-Mar	Active	Quiet
19-Mar	M-Class flare	Quiet
20-Mar	M-Class flare	Quiet
21-Mar	Active	Quiet
22-Mar	Active	Quiet
23-Mar	Active	Quiet
24-Mar	Active	Quiet
25-Mar	Active	Quiet
26-Mar	Active	Unsettled
27-Mar	Active	Quiet
28-Mar	Active	Quiet
29-Mar	Active	Quiet
30-Mar	Active	Quiet
31-Mar	M-Class flare	Quiet
1-Apr	M-Class flare	Quiet
2-Apr	M-Class flare	Quiet
3-Apr	Active	Quiet
4-Apr	Active	Quiet
5-Apr	Active	Unsettled
6-Apr	normal	Quiet
7-Apr	Active	Quiet
8-Apr	Active	Unsettled
9-Apr	Active	Quiet
10-Apr	Active	Quiet
11-Apr	Active	Quiet
12-Apr	Active	Storm
13-Apr	Active	Unsettled
14-Apr	Active	Quiet
15-Apr	Active	Quiet
16-Apr	Active	Quiet
17-Apr	Active	Quiet
18-Apr	M-Class flare	Quiet
19-Apr	Active	Quiet
20-Apr	Active	Storm
21-Apr	Active	Unsettled
22-Apr	Active	Unsettled

Date	X-Rays	Geomagnetic field
23-Apr	Active	Quiet
24-Apr	Active	Quiet
25-Apr	X-Class flare	Quiet
26-Apr	Active	Quiet
27-Apr	Normal	Quiet
28-Apr	Normal	Quiet
29-Apr	Active	Quiet
30-Apr	Active	Unsettled
1-May	Active	Quiet
2-May	Active	Quiet
3-May	Active	Quiet
4-May	Active	Unsettled
5-May	Active	Quiet
6-May	M-Class flare	Quiet
7-May	M-Class flare	Quiet
8-May	Active	Quiet
9-May	Active	Unsettled
10-May	Active	Quiet
11-May	Active	Quiet
12-May	Active	Quiet
13-May	Active	Quiet
14-May	Active	Quiet
15-May	Active	Quiet
16-May	Active	Quiet
17-May	Active	Quiet
18-May	Normal	Quiet
19-May	Normal	Quiet

CONCLUSION

The research as performed focused on investigating some parameters (e.g. canopy spacing; presence of flowers) that might influence the ability of two object-based methods to count plants in an open-field container nursery. Although some of the experiments used a UAV to obtain images, in the long term other methods (e.g. mobile boom) may be more appropriate for this application, although the economics of this approach will need to be evaluated. A UAV is simply one method to collect requisite images. The major benefit of this research was to begin evaluating software as a means to automate the counting process of plants in open-field nurseries. These studies also evaluate the utility of using off-the-self color camera for inventory management purposes.

In general, as the canopy separation (5 cm between canopy edges, canopy edges touching, and 5 cm of canopy edge overlap) and UAV flight altitude (22 m, 12 m, 6 m) decreased, total count error increased when data were analyzed using FA regardless of ground cover. The observation that the lower flight altitude (i.e. higher image resolution) resulted in lower count accuracy was unexpected. A similar conclusion was reached in a preliminary experiment at Lake Alfred, FL in 2012 using a different container plant (data not shown). Although count accuracy for plants placed on gravel was lower than for plants placed on black fabric, this was not related to ground cover type but more likely a result of variation in spatial resolution. When Thuja Firechief™ was used as the experimental plant, there was no visible effect of ground cover type (black fabric and gravel) on counting accuracy, however, due to the wide range in color and texture of ornamental plants, other plant types should be evaluated. Consistency of spatial resolution is desirable since it improves results when the algorithm is applied to different images. The lack of consistent spatial resolution in this study using was due to the UAV not being able to hold a precise altitude, although hardware and software is constantly being developed in order to improve the performance of UAVs. The UAV held a more precise altitude when images were taken of plants on black fabric, resulting in higher count accuracies. The algorithm trained in MATLAB yielded lower total count error than FA when gravel was used as the ground cover; this may indicate that spatial resolution plays a less critical role. Further research should be conducted to evaluate the specific effect of the variation in spatial resolution on count accuracy when a single algorithm is applied. At this time, a number of software and hardware improvements need to be made and tested to current UAVs before they can be reliably adapted for this use. The canopy width for nursery plants is typically smaller than for forest trees, suggesting the need for higher spatial resolution images which provides a strong justification for using a UAV in nurseries.

FA is easy to use but several parameters had to be changed when training the algorithm requiring a great amount of time. While FA generated good counting results, MATLAB algorithm yielded better overall count accuracy for plants placed on gravel as a result of a ratio obtained from images for plants placed on black fabric. The addition of this correction ratio, suggests that data from previous images could be used to increase count accuracy. Based on the combined result from these separate experiments, both algorithms appear to be fairly robust. It would be difficult to establish an exact cost for each method as the actual value will be determined by factors such as discounts, number of users, and the actual cost of the output program writing using MATLAB.

With the exception of the algorithm trained using non-flowering roses, results from data analyzed using FA were not influenced by plant canopy shape, plant status and presence of flowers when using images taken at 12 m above ground. The algorithm trained in MATLAB did not find any differences when plant canopy shape and presence of flower were evaluated for the species studied. Factors such as canopy shape, presence of flowers and plant status were evaluated independently, however in a commercial nursery setting, these and many other factors (e.g. slope of production area, variation in canopy size and plant height) might be involved and need to be evaluated.

Continued research with FA and the customizable algorithm trained in MATLAB are likely to improve future plant counting efforts by reducing the requirement for manual labor in the counting process. Based on the preliminary results from this study, further research is required to improve counting results using different algorithms, sensors (resolution, image distortion, angle of view, multi spectral and/or narrow bands), methods to obtain images, and environmental conditions (light variations –sun angle, shadows-, moisture on the ground cover).

Repeating the experiments over a longer period of time would allow us to extend the conclusions related to the settings in which the counting algorithms could be used; factors such as light conditions and sun angle would be added in the experiment, therefore, the variability of this factor would result in a broader generalization/applicability of the results. Collecting images for counting purposes could result in images with variation on environmental conditions regardless of the images being taken during the same day, especially in large nurseries where more time would be required to take the images.

Although results from these experiments have advanced our knowledge on certain parameters (e.g. two object-based methods; UAV versus boom lift; plant shape), our conclusions are limited to the conditions and parameters studied. Many more experiments need to be conducted before we can determine if this technique can be used to count plants in open-field nurseries in a commercial setting.

GLOSSARY

Aggregation: a tool in FA that allows the operator to fill holes or remove polygons that fail to meet the specified size requirement. Aggregation is a quick way to reduce clutter.

Automated feature extraction (AFE): a project file in FA that tracks the steps and settings used during a workflow.

Batch processing: a tool in FA that allows the operator to use an existing learning model to extract the same target features from several images.

Binarization: the act of transforming colored features of an object into vectors of numbers, most often binary vectors, to make good examples for algorithm classification.

Border index: feature that describes how jagged an image object is; the more jagged, the higher its border index.

Digitization: the representation of an object or image, by a discrete set of its points or samples.

Dilation: a FA raster tool used to expand features. Dilation implements a binary morphology filter that buffers pixel regions by the width of one pixel (repetitively for the specified number of cycles).

Elliptic fit: feature that describes how well an image object fit into an ellipse of similar size and proportions.

Erosion: FA raster tool used to shrink feature result polygons. It implements a binary morphology filter that strips away the outer layer of pixels (repetitively for the specified number of cycles) from the pixel region in a raster image.

Feature extraction: in pattern recognition and in image processing, feature extraction is a special form of dimensional reduction.

Feature class: file created in FA to store datasets.

Feature selector: pre-defined extraction options in FA designed to generate the quickest feature extraction based on the characteristics of each feature type.

Linear discriminant analysis: Linear discriminant analysis (LDA) and the related Fisher's linear discriminant are methods used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events.

Homogeneity criterion: term used in eCognition to describe the object homogeneity to which the scale parameter refers. Homogeneity criterion include shape (it modifies the relationship between shape and color criteria) and compactness (it optimizes objects with regard to compactness).

Input representation: spatial component that defines how FA will look, at and learn, from pixels of an image in order to distinguish between features.

Laser scanning: the process of shining a structured laser line over the surface of an object in order to collect 3-dimensional data. The surface data are captured by a camera sensor mounted in the laser scanner which records accurate dense 3D points in space.

Local maxima: the value of a function at a certain point in its domain, which is greater than or equal to the values at all other points in the immediate vicinity of the point.

Manhattan: input representation pattern used in FA to extract natural, impermeable features.

Multiresolution segmentation: procedure that locally minimizes the average heterogeneity of a given object for a given resolution of image objects.

Nadir point: the point on the ground vertically beneath the perspective center of the camera lens.

Natural feature selector: selector used in FA to extract individual trees, shrubs or other individual natural features.

Object-based image analysis (OBIA): a technique used to analyze digital imagery developed relatively recently compared to traditional pixel-based image analysis. While pixel-based image analysis is based on the information in each pixel, object-based image analysis is based on information from a set of similar pixels called objects or image objects. More specifically, image objects are groups of pixels that are similar to one another based on a measure of spectral properties (i.e., color), size, shape, and texture, as well as context from a neighborhood surrounding the pixels.

Opening: procedure that remove pixels from objects.

Omission error: error caused when an object is not count.

Panchromatic image/data: A single band image generally displayed as shades of gray.

Radial relief displacement: the apparent leaning away from the center point of vertical objects in an aerial photograph, due to the conical field of view of the camera lens.

Raster: A spatial data model that defines space as an array of equally sized cells arranged in rows and columns, and composed of single or multiple bands. Each cell contains an attribute value and location coordinates. Unlike a vector structure, which stores coordinates explicitly, raster coordinates are contained in the ordering of the matrix. Groups of cells that share the same value represent the same type of geographic feature. Raster datasets can be stored in many formats, including TIFF, JPEG 2000, Esri Grid, and MrSid.

Relative border to: object feature used in eCognition® to determine the relative border length an object shares with the objects of a given class.

Resampling: FA tool that allows the operator to alter the resolution of your images to improve results or to speed up the extraction process.

Rule set: a sequence of processes that are executed in a defined order.

Scale: eCognition® parameter that determines the maximum allowed heterogeneity for the resulting image objects.

Segmentation: the process of dividing an image into multiple parts. This is typically used to identify objects or other relevant information in digital images.

Smoothing: FA tool that reduces the number of vertices in a polygon.

Spatial resolution: The dimensions represented by each cell or pixel in a raster.

Spectral signature: The pattern of electromagnetic radiation that identifies a chemical or compound. Materials can be distinguished from one another by examining which portions of the spectrum they reflect and absorb.

Supervised learning: type of machine learning algorithm that uses a known dataset (called the training dataset) to make predictions.

Texture: A digital representation of the surface of a feature.

Training set/data: examples of target features used in the feature extraction process or set of plants used to create training samples.

Vector: A coordinate-based data model that represents geographic features as points, lines, and polygons. Each point feature is represented as a single coordinate pair, while line and polygon features are represented as ordered lists of vertices. Attributes are associated with each vector feature, as opposed to a raster data model, which associates attributes with grid cells.

Create vector metrics: FA analyst tool that allows the operator to calculate metrics for the features in your vector layers, including area, perimeter, etc.