APPLICATION OF HIGH RESOLUTION AERIAL IMAGING FOR INVENTORY MANAGEMENT IN NURSERIES AND CITRUS GROVES

By

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To my parents and friends
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APPLICATION OF HIGH RESOLUTION AERIAL IMAGING FOR INVENTORY MANAGEMENT IN NURSERIES AND CITRUS GROVES

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Nursery production is a large industry in the United States. Inventory data of container nurseries is crucial for growers for management purposes. Aerial imaging has the advantage of covering the field in short time. The first objective is to conduct container nursery inventory management with UAV systems.

The most common background in nursery industry is black fabric. However, there are large variations of ground cover, plant size, taxa, and production technique across nursery operations. Therefore, it is difficult to find a generic classification algorithm for all cases. Three representative categories which include yellow, green, and flowering nursery were chosen. Vegetation index and machine learning were used for classification. Classification models were built and the overall classification accuracies of higher than 97% were obtained for each case.

An algorithm based on canopy (base) area was developed for nursery counting. Counting variation regarding the fluctuation of the base area was discussed. The developed algorithm was tested on images captured at different heights and on blocks
with different container spacing and with different backgrounds. Results showed that container spacing and the interaction of spacing and background had significant effect on counting accuracy. To mimic the shipping and moving process, different sparse blocks were created. Results showed that the sparser the nursery block, the more accurate the counting. Also, to test the stability of the algorithm, the counting accuracy for irregular and regular shaped plants were compared as well as those of flowering and non-flowering plants. Finally, the algorithm was applied to a commercial nursery field. Counting accuracy was higher than 92% for all scenarios.

Citrus tree inventory management is the second part of this research. Modified color imagery at 2,500 feet and 3,500 feet was used for citrus tree counting considering the complex background. Graph cut was used for segmentation purposes. Three counting schemes based on canopy area, planting spacing, and projection were compared. The results show a correlation coefficient between ground counting and automated counting at 2,500 feet of 0.988 (area), 0.998 (spacing), and 0.993 (projection) and at 3,500 feet of 0.905 (area), 0.975 (spacing) and 0.955 (projection), respectively.
CHAPTER 1
INTRODUCTION

The subject of this dissertation is the application of high resolution aerial imaging on open field nursery container and citrus tree inventory management. There exists a large variation of ground cover, plant size, taxa, and production techniques across nursery operations. In order to test the generality of the algorithm, images of nurseries with different color (color variation), shape (shape variations), ground cover (background variation), arranging spacing (block density variation), and sparse arrangement (absence variation) were collected. In addition, image resolution variation was taken into account by collecting the images at different altitudes. True color image is capable of distinguishing nursery plants from background due to the uniform background used in US nursery production. However, true color imagery is not capable of differentiating the citrus trees from the background because of the complex backgrounds in citrus grove. Therefore, modified color imagery was used for citrus groves. The near-infrared (NIR) band was included considering the high reflectance of NIR energy for green plants. The developed algorithm was evaluated at different flying altitudes.

1.1 Dissertation Organization

The first chapter consists of a general introduction and a glance at precision agriculture, nursery production, and citrus production in US, remote sensing, and aerial platforms. The second chapter serves as a detailed literature review on the limitations and potential of applying remote sensing in agriculture, applications of UAV in agriculture, and applications of image processing technology in fruit count estimation. The third chapter focuses on developing segmentation methods for three representative
container nurseries. The fourth chapter describes a counting algorithm. Special focus is given on testing the developed algorithm on different image resolution, background, container plants density, irregular and regular shaped plants, flowering and non-flowering plants, and practical fields. The fifth chapter discusses using modified color image for citrus tree detection and developing an algorithm for citrus tree counting targeting at groves with prior knowledge (planting distance and planting year). The developed algorithm was tested on citrus groves at different flying attitudes. The final conclusions and suggestions for further improvement are included.

1.2 Nursery Production in US and Florida

The total sale of nursery crops reached $4.27 billion in 2014 (USDA Census of Horticultural Specialties, 2015). California, Florida, and Oregon are the top three states in terms of sales, accounting for 22%, 13%, and 11% of the total sales, respectively. Broadleaf evergreens (azalea), fruit and plants, deciduous shrubs (roses), and coniferous evergreens (arborvitae, juniperus) are the top four categories being sold in 2014, accounting for 19%, 18%, 16%, and 13% of the total sales. Container nurseries are the main sale category compared to bare root, balled, and burlapped, with a share of 63% of total sales. The total area in production with sales over $10,000 is about 471,106 acres and the production area in Florida is about 40,706 acres. The number of plants on January 1, 2006 in Florida was about 65,000,000 plants including broadleaf evergreens, coniferous evergreens, deciduous flowering trees, deciduous shade trees, deciduous shrubs, fruit and nut plants, and ornamental grasses. Crop production is a compact setting considering the number of plants and the area it takes. It is a high-value industry. There are about 7,300 producers with sales of more than $10,000 in 17 surveyed states, and Florida accounts for the largest portion with about 1,300 producers.
The nursery industry creates thousands of jobs with a total of 112,672 employees in 2006.

1.3 Citrus Production in US and Florida

Brazil, China, and the US are the top three citrus production countries. The total production in 2014-2015 for USA was about 9 million tons (USDA, 2016). Florida, California, Texas, and Arizona are the major citrus producing states in United States. In the 2014-2015 growing season, Florida produced 56% of the total citrus; California produced 40%, with Texas and Arizona producing the remaining 4%. The whole citrus industry has about a $9 billion economic impact in Florida. In 2015, 501,396 acres of citrus groves and over 66.8 million citrus trees in Florida were reported of which about 61 million are bearing trees (USDA, 2016). Usually, citrus trees start to bear fruits three years after planting. The estimated number of the bearing trees is very important in forecasting citrus production (in boxes) as shown in Eq. (1-1) (USDA, 2015). An accurate estimate of production could help growers to determine the best harvest time according to the price market which would maximize their profits. Currently, the inventory data are obtained via a comparison procedure (USDA, 2014). All maps records and a base image are transferred to a geographic information system (GIS). If any change is detected by the photo interpreter between digital images taken at different times, manual scouting will be conducted to get a revised count.

\[
\text{Production} = \frac{\text{Bearing Trees} \times \text{Fruit per Tree} \times \text{Percent Remaining at Harvest}}{\text{Pieces of Fruit per Box}} \quad (1-1)
\]
1.4 Remote Sensing

Remote sensing provides the ability to detect objects without contact. Depending on the source of light, sensors are classified as passive or active. Passive sensors measure the reflected or emitted energy of the objects which originate from the sun. Active sensors provide their own signal sources and then measure the reflected radiation from the target.

Human eyes are only sensitive to the visible band (380 nm-750 nm), which is a narrow range of the whole light spectrum. By applying different filters on sensors, sensors could “see” the characteristics of the target at other bands. Since the chemical components of objects are different from each other, their spectral signatures greatly differ as well. Remote sensing could help detect, discriminate, and observe objects in sensitive bands. It has a broad application in astronomy, mineralogy, medical, agriculture. To cover a large area fast and efficiently with remote sensing technology, aerial platforms are needed.

1.5 Aerial Platforms

Many types of aerial platforms exist, such as satellite, balloon, manned aircraft, and unmanned aircraft. Each platform has advantages and disadvantages depending on the specific application. For example, the Landsat 8 satellite images are available to download at no charge and they cover many bands which include but are not limited to Red, Green, Blue, NIR, shortwave infrared (SWIR), and thermal infrared (TIR). However, it takes 16 days to return to the same location. If a frequent monitoring is required, the satellite images are not a perfect fit. Unmanned aircraft is able to provide aerial images with high spatial and temporal resolution. However, with unmanned aircrafts, the battery
needs to be changed in a relatively short time which may complicate the flight process, and the payload is another concern if multiple cameras are onboard.

Several factors should be taken into consideration when choosing the aerial platform. Spatial resolution, which is defined as the actual size on the ground of one pixel, is one of the most important considerations. Temporal resolution which specifies the revisiting frequency for a specific location is also important if a frequent visit is needed. The cost of the platform is highly related to the budget and need to be considered. In addition, payloads of the platform, ease of flying, and flying regulations also need to be considered before flight.
CHAPTER 2
LITERATURE REVIEW

2.1 Limitations and Potentials of Applying Remote Sensing in Agriculture

Remote sensing came into use in agricultural applications in the 1920s. Early research proved that aerial images could be used to study plant diseases (Brenchley, 1966; Manzer et al., 1972; Greaves et al., 1983). More recent research has exhibited the comprehensive ability of aerial photography to assess plant condition and estimate yield and aerial biomass (Reid et al., 2016; Vega et al., 2015). However, high cost and relatively low spatial and temporal resolution limited extensive use of remote sensing systems by growers. Currently, researchers and very few large-scale growers obtain aerial images from commercial companies. Small-scale growers cannot afford them. Grenzdorffer et al. (2008) pointed out that high temporal resolution images are difficult and costly to obtain, either by satellite imagery or by conventional airborne data. Although spatial resolution has been improved in satellite sensors such as Ikonos (panchromatic: 0.8 m) or Quickbird (panchromatic: 0.65 m), it cannot meet the requirements of some practical applications that rely on specific spectral bands or very high resolution (2 inches or less). Unmanned aerial vehicle (UAV) systems could provide low-cost and high-resolution aerial images, overcoming the major deficiencies of the current image acquisition system (Berni et al., 2009). Matese et al. (2015) pointed out that the UAV is the most cost efficient platform compared to aircraft and satellite on small fields (5 ha). High temporal resolution comes from their short turnaround time and the convenience of repeated flights. This makes them perfect for agricultural applications because frequent observations are often required to monitor a field on an ‘as needed’ basis. The flexibility of mounting any tailored sensor on a UAV system could
help provide information geared toward the user’s needs. There are some more attractive features of UAV systems, such as the ability to fly close to the object from different positions at a low altitude, and decimeter accuracy navigation even with low cost GPS systems (Eisenbeiss, 2004). Most previous studies on remote sensing have been done using aerial or satellite imagery. Small UAVs can offer new possibilities such as very high resolution images which can provide possibility of increasing the detection accuracy or new applications that are not currently possible with the existing imaging system; at the same time it can initiate new challenges such as how to cover a larger area and deal with the issues related to stitched images.

2.2 The Application of UAVs in Agriculture

According to a report by the Association for Unmanned Vehicle Systems International (AUVSI) which shows the expected annual UAV sales for agriculture, public safety, and other markets from 2015 to 2025 (Figure 2-1), it is expected that the application of UAVs will be dominated by agriculture in the near ten years. In recent years, UAVs have shown great potential in different agriculture applications.

2.2.1 Yield Estimation

A regression model was built that relates NDVI and rice yield (Swain et al., 2010). Herwitz et al. (2002) reported a positive relationship between the reflectance of coffee tree canopies and ripened coffee yield. Relationship between fruit yield of citrus trees and number of orange pixels per image was studied by MacArthur et al. (2006). Research by Yang et al. (2001) targeted estimation of cotton yield from reflectance of spectral bands and the vegetation index extracted from UAV images. Similar research by Zarco-Tejada et al. (2005) explored the correlations of more indices from UAV images and cotton yield at different growth stages. Moreover, research on topics such
as determining the best harvest time (Johnson et al., 2003) and monitoring coffee ripeness (Johnson et al., 2004) provided important guidance on yield estimation.

2.2.2 Weed Detection

Weeds are one of the most serious threats to crops. They hinder the growth of native crops and degrade production. Automatic weed detection and management is desirable. UAVs provide the capability of detecting weeds in a low-cost, highly efficient way. Multi-spectral and hyperspectral sensors make it possible to discriminate weeds from plants. A variety of studies have proven that UAV systems can be successfully applied for weed detection (Hardin et al., 2007; Kazmi et al., 2011; Ghalenoei et al., 2009; Torres-Sánchez et al., 2013; Herwitz et al., 2004; Peña et al., 2013).

2.2.3 Disease and Stress Detection

UAV systems with different target sensors are used for disease detection. Many studies have been performed on this topic: citrus greening detection in citrus (García-Ruiz et al., 2013), verticillium wilt detection in olive trees, and downy mildew in opium poppy fields (Calderón et al., 2013, 2014).

UAV platforms with thermal sensors provide the possibility of monitoring the water status of large fields in a short time. Canopy temperature is a good indicator of crop water stress. Canopy temperature and other thermal information, such as the crop water stress index (CWSI), can be estimated from thermal images. They have been used to evaluate water stress of the following: olive orchards (Sepulcre-Canto et al., 2006), almond trees (Gonzalez-Dugo et al., 2012), cotton (Sullivan et al., 2007), and orchards composed of almond, apricot, peach, lemon, and orange trees (Gonzalez-Dugo et al., 2013). Aside from thermal information, other stress indices are commonly used for assessing water status, such as photochemical reflectance index (PRI),
chlorophyll ratio (R700/R670), and normalized difference vegetation index (NDVI). Calculations of these indices are based on spectral reflectance at specific wavelengths. Hence, combining thermal and multispectral or hyperspectral sensors together is a new trend in detecting water stress. This technology has been used to monitor water status in the following: citrus orchards (Stagakis et al., 2012; Zarco-Tejada et al., 2012), vegetation and crops (Berni et al. 2009; Xiang and Tian 2011; Swain et al., 2007), citrus leaves (Johnson et al., 2013), and water stress caused by verticillium wilt in olive (Calderon et al., 2014).

2.2.4 Drainage and Irrigation

To increase water efficiency and reduce water wastage, water management and irrigation control is important. Manual management is labor intensive since irrigation systems are usually large-scale. UAV systems are capable of covering a large area in a short time, although post-processing technology (such as image stitching) is needed. Such research was done by Chao et al. (2008).

2.3 Application of Image Processing Technology in Fruit Count Estimation

Similar to inventory management in nursery crops, counting fruit based on imagery has been reported in recent years to provide early estimates of fruit counts before harvesting which could improve strategies employed in fruit thinning, harvesting, packing, and storage. Stajnko et al. (2004) reported apple number estimates based on normalized index (NDI) and template matching with thermal images. Wang et al. (2013) used saturation, hue, and local maximum of specular reflections in four directions to detect apple pixels and then split touching apples and merged the occluded apple parts based on estimated diameter. Payne et al. (2013) segmented images of mango fruits and background with color information in RGB and YCbCr space and texture.
information. Then, a lower and an upper limit were applied on the block size to estimate mango number. An automated kiwifruit counting technique was proposed by Wijethunga et al. (2008). Kiwifruit was firstly extracted by minimum distance classification in L*a*b color space, and then a regression relationship was utilized to estimate the true fruit count. Nuske et al. (2011) detected grape locations using radial symmetry transformation and removed false position locations based on cluster size. Annamalai (2004) developed a citrus yield estimate system based on color images. Citrus fruits were extracted from background with hue and saturation information, and counting was conducted on the segmentation results. Kurtulmus et al. (2014) detected green citrus fruit with eigenfruit, color, and circular Gabor texture features. For counting citrus fruits, blob analysis was performed to merge multiple detections for the same fruit. Similar merge scheme was used by Silwal et al. (2014) to estimate apple fruits which were partially occluded.

In fruit counting, algorithm development mainly includes two main parts: (1) classification/detection of fruits from background and (2) development of counting scheme. The (1) selection of classification is application-dependent and different classification methods have been used to detect and distinguish leaves, fruits, trees, and weeds. For (2) development of a counting scheme, most work has focused on merging occluded fruits to avoid duplicate counting. Although some studies have dealt with touching fruits (Wang et al., 2013), those studies hypothesized that only two fruits, rather than multiple fruits, need to be split in fruit counts. The counting schemes in the fruit counting cannot apply to nursery production because more severe cases of canopy
interaction (overlap and touching) exist. Therefore, a better split mechanism is expected for inventory management in nursery production.

Figure 2-1. Predicted annual UAV sales for agriculture, public safety, and other markets in the US. AUVSI Economic Report. March, 2013.
CHAPTER 3
ASSESMENT OF SEGMENTATION METHODS OF NURSERY PLANTS

3.1 Background

Image classification and image segmentation are two related concepts. Segmentation implies a classification. Classification labels each point into a certain class which results in dividing images into several homogeneous regions and implicitly segments the image. This technology has been broadly applied in different areas, such as medical (Alirezaie et al., 1997; Sharma and Aggarwal, 2010; Wong, et al., 2002; Wang, et al., 2001), weather forecasting (Leung and Jordan, 1995; Lakshmanan et al., 2003), and fire detection (Chen et al., 2004; Giglio et al., 2003). Currently, there are many algorithms and techniques available for image segmentation purposes, such as support vector machine (Chapelle et al., 1999; Lin et al., 2011), neutral network (Skourikhine et al., 2000; Park et al., 2004; Kobashi et al., 2001), graph cut (Salah et al., 2011; Boykov and Funka-Lea, 2006), watershed (Haris et al., 1998; Lin et al., 2006; Bleau and Leon, 2000), thresholding (Perez and Gonzalez, 1987; Kapur, et al., 1985), and K-means (Ng et al., 2006; Chen et al., 2008; Kanungo et al., 2002). The selection of the algorithm is application-independent. For example, if the features of different classes in an image are similar in color, shape, and texture, then a more sophisticated classification algorithm may be required. However, in most situations, the selection of the best algorithm is a trade-off between performance and time complexity. The overall selection criteria is to obtain a satisfactory segmentation result in a time efficient way.

For images in which only certain parts are of interest, image segmentation or classification is the first step for further analysis. It helps extract foreground regions (region of interest) and masks background regions. In agriculture, image segmentation
and classification play a very important role. Leinonen and Jones (2004) applied a spectral angle mapper and minimal distance to segment the leaf region and background to identify plant water stress. Yang (2013) compared a Bayesian classifier and support vector machine for blueberry detection using features in original NIR-R-G color space and transformed color space. Wang (2009) applied support vector machine with color and shape properties for apple recognition. Hernández-Hernández et al. (2016) used a training algorithm to select the optimal color space and combined channels for plant/soil segmentation. Lesquerella flowers were segmented in hue, saturation, and intensity (HSI) color space to assess the flowering responses to variable irrigation and N fertilizer management (Thorpe et al., 2016).

Nursery production is a huge industry which contains many categories, such as broadleaf evergreens, deciduous shrubs, deciduous shade trees, and coniferous evergreens. Each category includes different species and each species may be at different growth stages. All these factors create the variation of nursery in color, shape, canopy area, etc. Therefore, it is thought to be impossible to develop a generic segmentation method for all container nurseries. However, there is one favorable factor for image segmentation of nursery plants which is that field container-grown nursery plants are mainly planted on black polypropylene fabric in the US for erosion control and prevention of weeds under and between the containers (Newman and Davies, 1988). The black cover would create a uniform mask, thus simplifying the background. In this chapter, image segmentation methods of three representative plants on black fabric will be developed and evaluated. The segmentation results will serve as a basis to the counting method in the next chapter. To understand how image resolution will affect
segmentation accuracy, segmentation accuracies at different capturing altitudes will be compared in this chapter.

The objectives of this study are 1) to build robust classifiers to separate different container nursery plants from background for selected species; 2) to evaluate the segmentation accuracy at different altitudes. The results of this study will be used for inventory estimate of container nursery plants.

### 3.2 Material and Methods

#### 3.2.1 Image Collection

To develop and evaluate different classification methods for different cases, three representative cases were selected: perennial peanut (green), arborvitae (yellow), and Coral Drift® rose (green with flowers).

Images of perennial peanut (*Arachis glabrata*) were collected on November 13, 2012 at the Citrus Research and Education Center of the University of Florida (Lake Alfred, FL, USA). The experimental field was a block of 100 containers spaced in a 10 × 10 grid on black fabric background. An 800AJ articulated boom (JLG Industries, Inc., McConnellsburg, PA) was used as image capturing platform. The sensor used was a Canon EOS 5D Mark II. It is a 21.1-megapixel (5,616 × 3,744 pixels) full-frame, CMOS, digital, single-lens reflex camera. The entire detailed experiment setting will be described in Chapter 4. At this point, only images with plants spaced at 18 cm (distance between the edges of adjacent containers) captured at 9, 12, 15, and 18 m were used to evaluate the classification method. The second dataset was collected on November 13, 2013 at Greenleaf Nursery, Park Hill, OK. The camera used was a Sony Alpha NEX-7 (Sony Corporation of America IR, San Diego, CA), 24.3 megapixels color digital frame camera. Images of Fire Chief™ arborvitae placed in an 8 × 8 grid were taken by
UAV system with black fabric background. Again, the details of the entire experiment setting will be described in Chapter 4. At this point, only images with plants spaced at 0 inches with a camera height of 6, 12, and 22 m were used for classifier evaluation purposes. In addition, to find the best classification method for flowering plants, images of Coral Drift ® rose (Rosa sp. ‘Meidrifora’) placed in an 8 × 8 grid with 5 cm spacing at 12 m were taken. The plants species, corresponding color, cover background, and capturing heights used in this chapter are shown in Table 3-1.

3.2.2 Pre-processing and Post-processing

Image pre-processing technologies were performed before image segmentation. A 3 × 3 median filter was used to remove noise while preserving edge information. To increase the image contrast, the upper 1% and lower 1% of gray scale data was mapped to 1 and 0, respectively. Data between the upper and lower boundary were mapped to (0, 1). Image post-processing technologies including erosion and dilation were also performed to remove small false identified blobs.

3.2.3 Classification or Segmentation Method

3.2.3.1 Index Thresholding

Thresholding is the most direct method for segmentation. In color image processing, not only the information of RGB space, but also information in other space, such as HSV, L*a*b, or YCbCr could be used. The basic idea of thresholding is to classify different classes based on the boundary values of a chosen component. The component could be a pure color component (red, saturation, brightness, etc.), or a combination of color components \((a \times r + b \times g + c \times b)\), or an index component \((NDVI = \frac{nir-r}{nir+r}, GNDVI = \frac{nir-g}{nir+g}\), etc.). Histograms of the chosen gray-scale components
of different classes will be built and threshold values will be set. A two-class classification scheme is shown below:

\[
\text{class} = \begin{cases} 
1, & \text{component value} < \text{threshold} \\
2, & \text{component value} \geq \text{threshold}
\end{cases}
\]

The accuracy of the segmentation is decided by the amount of separation of the histograms of different classes.

3.2.3.2 Support Vector Machine

There are two categories of classification methods: supervised classification and unsupervised classification. Unsupervised classification is a clustering process relying on unlabeled inputs. Supervised classification predicts the labels based on certain inputs and outputs. Support vector machine (SVM) (Vapnik, 1999) belongs to the supervised classification method and can be used for image classification. It originated from machine learning. The first step in SVM is to build training data which is composed of feature vectors together with known labels. The goal of SVM is to predict the unknown labels of the test data given only the feature vectors of the test data. Training data are represented as instance-label pairs \((x_i, y_i), i = 1, 2 \ldots l; x_i \in R_n \text{ (n is the feature dimension)}; y_i \in \{-1, 1\}\). The basic idea of SVM is to find the optimal maximum-margin hyperplane represented by Eq. (3-1) which could linearly separate the points labeled as -1 from the points labeled as 1 (Figure 3-1). Input vectors that lie on the decision boundaries are called support vectors.

\[
t_i = w \ast x_i + b
\]  

\(i\) where:

\(t_i\) is the separating hyperplane equation,

\(w\) is the weight vector,
$x_i$ is the feature vector,

$b$ is the bias.

The margin between the two hyperplanes is $\frac{2}{\|w\|}$. With the condition that:

for all points which are labeled as -1 ($y_i = -1$), $t_i \leq -1$;

for all points which are labeled as 1 ($y_i = 1$), $t_i \geq -1$

These two conditions are combined into $t_i * y_i \geq 1$, which indicates $y_i * (w * x_i + b) \geq 1$. So, the optimization function for SVM is $\arg\min \frac{\|w\|^2}{2}$, subject to (for any $i = 1,2 .. k$) $y_i * (w * x_i + b) \geq 1$.

This is a quadratic optimization problem and could be solved by the Lagrange multiplier approach (Haykin, 1998).

However, data points in the original feature space are sometimes not linearly separable. Then, the data is mapped with a mapping function $\varphi$ into a higher even infinite space where linear separation is possible. With kernel trick indicates, the exact mapping function does not need to be known because every dot product in mapped space can be replaced by a kernel function (Eq. 3-2).

$$k(x_1,x_2) = \varphi(x_1) \cdot \varphi(x_2)$$

(3-2)

where:

$\varphi(x_1)$ is the mapped vector of feature vector $x_1$;

$\varphi(x_2)$ is the mapped vector of feature vector $x_2$.

Since the quadratic optimization solution for SVM includes a term $x_1 \cdot x_2$, the solution in the mapped space will have a term $\varphi(x_1) \cdot \varphi(x_2)$. That is where the kernel function comes into play. The most common used kernel function is the Gaussian radial basic function which corresponds to an infinite feature space.
3.2.3.3 Classification Evaluation

To evaluate the classification accuracy, false negative and false positive rates of plant pixels were calculated. A false negative is defined as a plant pixel classified as a background pixel. A false positive is defined as a background pixel classified as a plant pixel. Five-thousand pixels in each category were chosen as ground truth data and compared with the segmentation result. The plant ground truth data was selected at leaf scale instead of plant scale because the canopy density does not provide total coverage of the soil or background. Since the SVM package already provides classification accuracy, only the segmentation accuracy will be evaluated for perennial peanut (green) at 9, 12, 15, and 18 m and for Fire Chief™ arborvitae (yellow) at 6, 12, and 22 m.

3.3 Results and Discussion

In this section, the segmentation methods will be evaluated on different data sets. Five-thousand test pixels of the foreground and background will be randomly chosen. When supervised classification is used, ten-thousand pixels for each class are randomly chosen, 80% of which are used for training purposes and 20% are used for testing purposes. False positive and false negative of the two categories will be calculated. False positive and false negative are used to indicate the quality of the classifier.

3.3.1 Classification of Perennial Peanut (*Arachis glabrata*) on Fabric

Green plants (foreground) and black fabric (background) has a large contrast in the visible spectrum. In RGB space, r, g, and b components of black are close to 0. However, for green plants, reflectance of the green band is larger than that of the red and blue bands. To highlight the green component, the gray scale component excess green index \(ExG = 2 \times g - r - b\) (Woebbecke et al., 1995, Ribeiro et al., 2005) was calculated. The ExG of black fabric will be near 0 while the ExG of green plants will be
substantially greater than 0. Five-thousand black fabric pixels and five-thousand green plants pixels were randomly chosen. The distribution of ExG for background and green plants are shown in Figure 3-2. From the figure, it can be clearly seen that there is no overlap between the histograms of the two classes. The ExG of green plants is much higher than that of the background. A global threshold was then generated to segment the image and false negative and false positive rates at each height, as shown in Table 3-2.

Table 3-2 shows that there were no background pixels that were misclassified as plants, while a few plant pixels were misclassified as background pixels. In addition, no strong relationship between the segmentation accuracy and collecting altitudes (image resolution) was observed. At the altitudes of 9 and 15 m, three out of five-thousand plants pixels are misclassified as background. At the altitudes of 12 and 18 m, there were no misclassified pixels. The reason for this may be because the gap of ExG between the plants and background is large enough so that resolution is not a dominant factor in deciding segmentation accuracy. In summary, the observed segmentation accuracy was higher than 99%.

3.3.2 Classification of Fire Chief™ Arborvitae (Thuja occidentalis L.) on Fabric

For black fabric, the reflectance at red, green, and blue bands is close to zero. There is a large difference in the reflectance of red and blue bands for yellow objects. Normalized index $\frac{(r-b)}{(r+b)}$ was used to segment yellow objects from the background. When images were taken, shadows occurred on the background. The distribution of normalized index of yellow plants, background, and shadows are shown in Figure 3-3. It can be observed that the histogram of shadows interfered with both of plant and
background. However, the plants and background are completed separated. Based on the histogram, setting the threshold in the range of [0.05,0.30] could aid in removal of all background pixels and a portion of the shadow pixels. The next step was to separate the plants from the remaining shadow pixels. Since the shadow pixels are a dark color, index $3 - (r + b + g) - k \times (|r - b| + |g - b| + |r - g|)$ was taken to segment dark pixels from other pixels. This index was chosen because the $r$, $g$, $b$ components and the absolute difference between each of the two components are small for dark pixels. It could help to separate dark pixels from plant pixels. The value of $k$ is set to 10 via a trial and error process. The histograms of $3 - (r + b + g) - 10 \times (|r - b| + |g - b| + |r - g|)$ of the background and plant pixels are shown in Figure 3-4. By applying the index, the shadow pixels could be extracted. By overlaying the shadow pixels onto the image, which contains plants and part of the shadows, plant pixels could be successfully extracted. An example of the processing of an image is shown in Figure 3-5. The false negative and false positive rates of image segmentation at different image collecting altitudes are listed in Table 3-3.

From Table 3-3, it is clear that the false negative rate increased as image collecting altitudes increased. This is consistent with the assumption that the decreases in the spatial resolution will result in lower classification accuracy. However, the overall accuracy is greater than 99%.

### 3.3.3 Classification of Coral Drift ® Rose (*Rosa* sp. ‘Meidrifora’) on Fabric

For rose plants with flowers, the region of interest is a mixture of red flowers and green leaves. Support Vector Machine (SVM) was used for image classification. LIBSVM (Chang and Lin, 2011) was chosen to segment nursery plants from the
background. The Matlab package ‘LIBSVM’ was used for classification purposes. Firstly, 10,000 pixels of pure foreground (leaves and flowers) and 10,000 pixels of pure background were selected manually. Foreground pixels were labeled as 1 while background pixels were labeled as -1. A three-dimensional feature \( \{r,g,b\} \) space was created for the two categories. 80\% (8,000 pixels) of each category was used for training the model, and 20\% (2,000 pixels) of each category was used for the purpose of testing. The scatter plot of the feature vectors of the background and foreground can be visualized in Figure 3-6. Before applying SVM, it is recommended to scale the attributes in the feature vector to [-1, 1] or [0, 1] to avoid attributes with a large number of dominating attributes with a small number (Hsu et al., 2003). In this research, the value of \( r, g \) and \( b \) is already in the range of [0, 1]; therefore, scaling is not needed.

From the feature space, it is observed that separation of these two categories with a linear classifier is not possible. Hence, a kernel function was applied to transform the original data into a higher dimension space. Since the feature dimension is much smaller than the training size, the RBF kernel is recommended. RBF kernel is represented as \( e^{-\gamma |\mu - \nu|^2} \). Two parameters including (1) penalty parameter \( C \) and (2) kernel parameter \( \gamma \) for the RBF kernel need be determined. The penalty parameter \( C \) is a trade-off between the margin width of the two categories and the number of outliers. To choose the best parameters, a 10-fold cross validation was applied. Figure 3-7 shows the grid search approach which was used to find the \((C, \gamma)\) pair with the best cross validation accuracy. The results indicated that the parameter pair (16,8) had the highest cross-validation accuracy 97.9\% and was used to build the classifier with all of the training data. Furthermore, the classifier was used to predict test instances with
unknown labels. The classification accuracy for the test data was 97.6% (3,902 / 4,000). Then, the built classifier was applied to the collected image. Figure 3-8 shows an example of the original image and the binary segmented image.

From the comparison between the original and segmented image, it can be observed that leaves and flowers are successfully extracted from the background and shadows of the plants. Even the petals that fell on the fabric are detected. The yellow grid lines on the fabric are also classified as plants. This is because the leaves (green) and flowers (red) were merged together as one category. Their \( \{r, g, b\} \) feature space will cover the feature space of yellow color. However, since the grid line is thin, it is removed by the erosion operation with a disk size of 2.

### 3.4 Conclusions

In this chapter, three representative taxa were selected which includes green foliage, yellow foliage, and flowering plants. Different classification methods based on index thresholding and SVM were developed for each category (Table 3-4). The classification accuracy on a pixel-based level was evaluated. The ground truth data was manually chosen within the image. For perennial peanut and arborvitae, the classification accuracies at different altitudes were evaluated. For the green foliage of perennial peanut, the false negative rate was approximately about 2 in 5,000 with no false positive pixels. For the yellow foliage arborvitae, the segmentation accuracy decreased as the height increased. The false negative value increased from 1 in 5,000 to 32 in 5,000 when image collection altitude increased from 6 m to 22 m above the canopy. For rose, the overall accuracy of SVM segmentation was 97.5%.

The classifiers were built based on color information in which the background cover (black ground cloth) remained the same. In the future applications, if there are
plants with similar color as the representative plants studied here, the same classification method could be used and serve as a database for future use. The binary segmentation result will be used for count estimation in the next chapter.
Table 3-1. Plants, background, capturing altitude for evaluating classification method.

<table>
<thead>
<tr>
<th>Species</th>
<th>Color</th>
<th>Background</th>
<th>Height (m)</th>
<th>Spacing (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perennial peanut (Arachis glabrata)</td>
<td>Green</td>
<td>Fabric</td>
<td>9, 12, 15, 18</td>
<td>18</td>
</tr>
<tr>
<td>Fire Chief™ arborvitae (Thuja occidentalis L.)</td>
<td>Yellow</td>
<td>Fabric</td>
<td>6, 12, 22</td>
<td>0</td>
</tr>
<tr>
<td>Coral Drift ® rose (Rosa sp. 'Meidrifora ')</td>
<td>Green plants with flowers</td>
<td>Fabric</td>
<td>12</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 3-2. False negative and false positive rates of perennial peanut at each height.

<table>
<thead>
<tr>
<th>False negative</th>
<th>False positive</th>
<th>Height (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3/5000</td>
<td>0/5000</td>
<td>9</td>
</tr>
<tr>
<td>0/5000</td>
<td>0/5000</td>
<td>12</td>
</tr>
<tr>
<td>3/5000</td>
<td>0/5000</td>
<td>15</td>
</tr>
<tr>
<td>0/5000</td>
<td>0/5000</td>
<td>18</td>
</tr>
</tbody>
</table>

Table 3-3. False negative and false positive rates of Fire Chief™ arborvitae at each height.

<table>
<thead>
<tr>
<th>False negative</th>
<th>False positive</th>
<th>Height (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/5000</td>
<td>0/5000</td>
<td>6</td>
</tr>
<tr>
<td>6/5000</td>
<td>0/5000</td>
<td>12</td>
</tr>
<tr>
<td>32/5000</td>
<td>0/5000</td>
<td>22</td>
</tr>
</tbody>
</table>

Table 3-4. Segmentation method corresponding to each plant.

<table>
<thead>
<tr>
<th>Species</th>
<th>Segmentation method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perennial peanut (Arachis glabrata)</td>
<td>Index: ((2 \times g - r - b))</td>
</tr>
<tr>
<td>Fire Chief™ arborvitae (Thuja occidentalis L.)</td>
<td>Index: (\frac{(r-b)}{(r+b)}) and (3 - (r + b + g) - 10 \times (</td>
</tr>
<tr>
<td>Coral Drift ® rose (Rosa sp. 'Meidrifora ')</td>
<td>Support Vector Machine</td>
</tr>
</tbody>
</table>
Figure 3-1. SVM separating two classes in two-dimensional feature space.

Figure 3-2. Histograms of $(2 \times g - r - b)$ for plants and background.
Figure 3-3. Histograms of $\frac{(r-b)}{(r+b)}$ for plants, shadows, and background.

Figure 3-4. Histograms of $3 - (r + b + g) - 10 \times (|r - b| + |g - b| + |r - g|)$ for plants and background.
Figure 3-5. Overview of plant extraction process. A) original image, B) image extracted by index $\frac{r-b}{r+b}$ and C) removing remaining shadow pixels between plants from B.
Figure 3-6. Scatterplot of \{r, g, b\} features of plants and background pixels.

Best log2(C) = 4.0  log2(gamma) = 3  accuracy = 97.9188%
C = 16.0  gamma = 8

Cross validation accuracy
97.5  97  96.5  96  95.5  95

Figure 3-7. Parameter selection with grid-search approach.
Figure 3-8. Example of segmentation of flowering rose from background. A). Original image and B). Segmented binary image.
CHAPTER 4
DESIGN, GENERALITY, AND STABILITY OF COUNTING METHODOLOGY FOR NURSERY PLANTS

4.1 Background

Container nurseries are an example of compact and intensive agricultural production. Generally, one hectare of land may hold 80,000 to 600,000 containers (Lu et al., 2006). Management of containerized crop production is labor-intensive and time consuming (Sokkarie and Osborne, 1994), especially for large nursery production areas. Inventory is extrapolated on a count of only a portion of their crop (Hale, 1985) due to the time involved in manually counting each plant. Low accuracy is another limiting factor for this method considering the intensive labor involved in the count recording process in vast field areas.

One further step in automating inventory management is the occurrence of Radio Frequency Identification (RFID). However, RFID system works only when within close proximity (small read range) to avoid transmission error (Hartmann and Claiborne, 2007). Robbins and Leiva (2014) mentioned that the primary challenge of applying an RFID system to nursery production is to match the proper tag with different production systems and environmental conditions which makes RFID system less adaptive.

Research focusing on nursery inventory management with aerial-based approaches has emerged in response to the aforementioned limitations of ground-based approaches. Only one research study has reported using aerial imagery to count container-grown nursery plants; Leiva (2014) used Feature Analyst, an object-based image analysis (OBIA) software, to count open-field container nursery plants. However, this method requires subjective user input and parameter settings, which could be a source of error. In addition, the cost of this software is a concern for farmers who are
interested in only obtaining inventory data and would not utilize the other features of the software package. In this chapter, an open-source algorithm targeting only inventory management was developed in MATLAB 2013b.

In addition to the algorithm design, the effects of some important factors that affect the algorithm were evaluated herein. The first factor is altitude. By capturing images at different altitudes with a fixed camera, the effect of image resolution can be evaluated. The second factor is container plant spacing or density. Thirdly, the effect of the ground cover on counting accuracy was evaluated. Since container nursery plants are typically produced on black fabric or gravel, the accuracy will be compared on these two backgrounds. Fourthly, since the number of containers in a fixed block changes due to plant movement or shipping, different scenarios of missing containers were evaluated. Fifthly, there are some variations in the plants themselves. In this study, the variations are confined to the time of flower bloom and their shape. The performance of the counting scheme was evaluated on irregular and regular shaped plants as well as plants with and without flowers. Lastly, the algorithm was tested at a commercial nursery field for practical application.

In summary, the objectives of this study are 1) to develop a split scheme for severely touching canopies considering the compact setting in container-grown nurseries; 2) to evaluate the effect of flight altitude (image resolution) and container spacing/canopy density on the developed algorithm; 3) to evaluate the effect of ground cover (black fabric and gravel) on the algorithm; 4) to explore the versatility of the algorithm, specifically, to evaluate the performance on incomplete crop blocks and to see whether the counting algorithm is dependent on shape or growth stage.
4.2 Materials and Methods

4.2.1 Data Collection

4.2.1.1 Dataset 1. Investigation of the Effect of Flying Height and Container Spacing for Perennial Peanut

An 800AJ articulated boom (JLG Industries, Inc., McConnellsburg, PA) was used in this study (Figure 4-1). The experiment was conducted on 13 and 14 November 2012 at the Citrus Research and Education Center of the University of Florida (Lake Alfred, FL, USA). The available height range of the boom was 9.14 m to 24.38 m (30 to 80 ft.). Sensors were mounted on an aluminum pole that extended 2 m horizontally beyond the bucket of the boom. Images were taken after a proper height (altitude) and location were obtained by adjusting the extendable boom. A plumb line was used to locate the center of the plant region to guarantee that the image had complete coverage of all the plants.

The experimental field was a block of 100 containers spaced in a 10 × 10 container grid on a black fabric cover. Perennial peanut (*Arachis glabrata*) is a fast growing crop that has a uniform and regular outline to its canopy. The containers used were Nursery Supplies blow molded C200 pots with the following specifications: volume, 2.03 L; top diameter, 15.24 cm, and height, 15.24 cm. Images were taken at the vertical distances from the ground of 9, 12, 15, and 18 m (30, 40, 50, and 60 ft.). In addition, container spacing (distance between the edges of adjacent containers) of 0, 3, 8, 13, 18, and 23 cm (0, 1, 3, 5, 7, and 9 inches) which corresponds to plant density 43.0, 31.6, 19.1, 12.8, 9.2, 6.9 plants/m² were evaluated. Twenty-four treatments (4 heights × 6 plant densities) were evaluated with four replicates each. In order to validate the results, 20 plants were randomly chosen then switched with 20 other plants inside
the block after photographing each replicate. The center location of the 10 × 10 block was marked. Before each image was taken, the boom operator used a plumb line to check whether the camera was directly over the center point of a block in order to make sure the image did not deviate. Although this was done, some images still deviated due to camera orientation. The deviation reduced the available number of combined treatments to 17. The camera used in this experiment was a Canon EOS 5D Mark II with a resolution of 5,616 × 3,744 pixels.

4.2.1.2 Dataset 2. Evaluation of the Effect of a Partially Filled Block on Plant Count

The plant species, container size, and the articulated boom used for this dataset are the same as described in Dataset 1. The platform was fixed at 12 m (40 feet), and container spacing was set at 8 cm (3 in). Twenty plants were randomly moved out from the complete 10 × 10 block each cycle until only 20 plants remained. In total, there were four treatments in which 80, 60, 40, and 20 plants remained randomly spaced within the initial area of the 10 × 10 block. For each treatment, the plants were shuffled randomly three times. In each shuffling, plants were switched randomly so that not only the locations of the plants, but also the voids were always changing.

4.2.1.3 Dataset 3. Investigation of the Effect of Flying Height, Plant Spacing, and Ground Cover for Fire Chief™ Arborvitae

Container-grown Fire Chief™ arborvitae (Thuja occidentalis), growing in #3 black polyethylene containers (height: 23.5 cm, top diameter: 26.5 cm, and bottom diameter: 23.0 cm) were spaced in staggered rows to achieve three canopy separation treatments: 5 cm between canopy edges (completely separated), 0 cm between canopy edges (edge touching), and -5 cm between canopy edges (5 cm canopy edge overlap) which correspond to a plant density of 8.8, 11.9, and 17.6 plants/m², respectively. Three
treatment sets were replicated three times in a randomized complete block design (RCBD) for a total of nine sets of plants. For each set, 64 plants \((8 \times 8)\) were placed on gravel. One set with -5 cm canopy separation only had 56 plants \((7 \times 8)\) due to a miscounting when the experiment was set up. The nine sets were placed \(3 \times 3\). Four fully separated plants were placed outside each of the nine sets and were used to train the open-source MATLAB algorithm. The same canopy treatment was repeated on black polypropylene fabric ground cover (Lumite, Inc., Alto, GA, USA) by repositioning the plants on fabric cover.

In this dataset, instead of an articulated boom, a multi-rotor UAV was used. The sensor was a Sony NEX-5n 16.1 megapixels color digital frame camera with an 18-55 mm lens. Each flight was carried out in a zigzag pattern to cover all nine sets. The layout and flight path of the experiment are shown in Figure 4-2. The gray line represents the UAV flight path. To evaluate the effect of flight height, three flights with 6 m, 12 m, and 22 m were made on 13 July 2013 (gravel) and 14 July 2013 (fabric) at Greenleaf Nursery, Park Hill, OK, USA. The sky was sunny when images were taken. The flight at each of the three altitudes was executed two times with the same flight path. The first flight was referred as run 1 and second was referred as run 2.

**4.2.1.4 Dataset 4. Investigation of the Stability of Counting Methodology with Different Shapes and in Different Growing Stages**

Two species of Juniper (Juniperus chinensis ‘Sea Green’ and Juniperus horizontalis ‘Plumosa Compacta’) were selected to evaluate the effect of shape on plant counts. ‘Sea Green’ was chosen as the plant with an ‘irregular’ canopy shape while ‘Plumosa Compacta’ as the ‘regular’ shape. In addition, Drift® rose (Rosa sp. ‘Meidrifora’) was selected to evaluate the effect of presence of flowers. There were two
treatments for the roses: rose plants with flowers and rose plants without flowers. For roses without flowers, flowers were manually removed.

For each treatment in canopy shape and flowering, 64 plants (8 × 8) were placed with a 5 cm canopy separation on black polypropylene fabric ground cover. The two treatment sets in both experiments were replicated five times in a randomized complete block design (RCBD). Four plants of treatment 1 and four of treatment 2 were placed outside all sets for the purpose of developing and training an open-source MATLAB algorithm. A Bil-Jax 3632T boom lift (Haulotte Group, Archbold, OH, USA) fixed at 12 m above ground level was used to collect images on 13 November 2013 at Greenleaf Nursery, Park Hill, OK, USA. The sensor used in this experiment was a Sony Alpha NEX-7 (Sony Corporation of America IR, San Diego, CA, USA), 24.3 megapixels color digital frame camera with an 18-55 mm lens.

### 4.2.1.5 Dataset 5. Commercial Nursery Field Inventory Management

Aerial images were taken in Florida with a video camera on August 3, 2013 on gallon Ilex cornuta ‘Burfordii’ and Viburnum obovatum ‘Mrs. Schiller’s Delight’. The nursery crops were arranged in a rectangle. UAVs flew at a steady altitude of 17 meters from one end to another end. The video recorder used was Sony NEX-5n (Sony Corporation of America IR, San Diego, CA, USA). It autofocuses and MPEG-4 1,440 × 1,080 pixels were recorded at 30p on NTSC models. To guarantee a high overlap of the consecutive frames, the UAV system flew at a speed of 3 m/s. ICE (Microsoft, Inc.) was used to create the panoramic image of the nursery field, and the processing time was about 2 minutes.
4.2.2 Counting Methodology

Since detect each plant by pattern recognition is a great challenge due to the compact setting of nursery production, canopy area mapping is a good alternative by which to estimate count. To validate the canopy area mapping method, the first step is to determine the distribution of canopy area. If the area information is easy to estimate based on a certain parameter (for example, area could be calculated if diameter is available for plants with circular shape), the distribution of the plant area will be shown. However, like Juniperus (Figure 4-3), the ground leaf area is difficult to determine. The alternative is to find the distribution of the plant area in an image (in pixels) based on the segmentation method discussed in the previous chapter. Arborvitaes, Juniperus and roses placed on fabric were chosen as an example on which to check the distribution of the canopy area.

4.2.2.1 Distribution of Plant Areas on the Ground

In order to obtain the distribution of ground canopy area, two shoot diameters at directions perpendicular to each other were measured.

There were nine sets of arborvitae. For each set, the shoot diameter of four corner plants and one center plant were sampled and their diameters at two directions were measured. Since the shape of arborvitae is circular, the diameter of each plant (d) was calculated by taking the average value of the two diameter measurements. The canopy area of each plant was calculated by $\pi \times \left(\frac{d}{2}\right)^2$. In total, the canopy area of 45 plants in total will be calculated. The distribution of the canopy area is shown in Figure 4-4.
4.2.2.2 Distribution of Plant Areas within Images

The corresponding segmentation method for each plant that was covered in the last chapter and histograms of the canopy area of the training plants were created using images at 6 m (Figure 4-5 A), 12 m (Figure 4-5 B), 22 m-run 1 (Figure 4-5 C) and 22 m-run 2 (Figure 4-5 D). For 22 m, there are two peaks of the canopy area for run 1 and run 2. The possible reason for this is that the UAV did not hold a precise altitude due to wind. For Juniperus and roses, there were not many training plants available. Therefore, the boxplot with the mean and standard deviation of canopy area were created in the image of Juniperus in Figure 4-6 and roses in Figure 4-7.

4.2.2.3 Interval Counting

The arborvitae canopy area on the ground (mean: 1090.0 cm², standard deviation: 117.4 cm²) and in the image fit a Gaussian distribution (mean, 39,798 pixels and standard deviation, 10,587 pixels (6 m); mean, 15,244 pixels and standard deviation, 4,105 pixels (12 m); mean, 2,737 pixels and standard deviation, 262 pixels (22 m-Run 1); mean, 4,696 pixels and standard deviation, 465 pixels (22 m-Run 2). The boxplots of the mean and standard deviation of the canopy area in the image for irregular plants (mean, 12,050 pixels and standard deviation, 2,519 pixels), regular plants (mean, 9,682 pixels and standard deviation, 1,837 pixels), plants with flowers (mean, 20,478 pixels and standard deviation, 3,732 pixels) and plants without flowers (mean, 19,153 pixels and standard deviation, 1,035 pixels) also indicate the small variance in canopy area. Therefore, a counting algorithm was developed in MATLAB (R2013b) based on the assumption that the canopy area of container-grown plants has a small variance.
Conceptually, the goal of the MATLAB algorithm is for a crop producer to use only a small number of container-grown plants to obtain a canopy area estimate, which can then be utilized to train the algorithm to provide an accurate inventory estimate of large plant blocks comprised of container-grown plants. In this paper, four separate plants were placed outside region of interest (ROI). The classification result obtained from the proposed method was converted into a binary image in which pixels with digit number 1 (white pixels) represented a plant and pixels with digit number 0 (black pixels) represented the background. Data was then used to calculate the average canopy area (A) in the training set and propagate the canopy area (A) in the training set to the ROI:

1. Find the number of white regions ($k_0$) with area smaller than $0.5 \times A$;
2. Find the number of white regions ($k_1$) with area in the range of $0.5 \times A$ and $1.5 \times A$;
3. Find the number of white regions ($k_2$) with area in the range of $1.5 \times A$ and $2.5 \times A$;
4. Continue the process until all the white regions are included.
5. The total count will be the summation of plants in each region $0 \times k_0 + 1 \times k_1 + 2 \times k_2 + \cdots$.

The flowchart of this process is shown in Figure 4-8.

4.3 Results and Discussion

4.3.1 Algorithm Stability

4.3.1.1 Effect of Height and Container Spacing for Perennial Peanut (*Arachis glabrata*)

The plant blocks for some treatments (container separation (cm), flight altitude (m)) are not included in the image due to the shift of capturing system. Their treatments include (0,15), (3,15), (8,15), (0,18), (3,18) and (8,18). In addition, only seven rows (70 containers) are included in the image for treatment (13,18). There are four replicates for each treatment. The assumption is that the counting results are normally distributed. In
order to test whether a population mean is equal to a specified value, the t-test is used. A 95% confidence interval for the mean will be \([\bar{x} - (se \times 3.182), \bar{x} + (se \times 3.182)]\). (The critical value of t for a 95% confidence interval for 3 degrees of freedom is 3.182).

\[
\text{where } se = \frac{s}{\sqrt{n}}; s = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^2}.
\]

Table 4-1 shows the 95% confidence interval for four automated counts for each treatment. If data is not available at certain treatment, the cell is marked as NA.

In total, there are nine out of 18 confidence intervals which do not contain the ground truth data. All confidence intervals with container separations of 0 and 3 cm do not contain the manual data, and the automated count has a severe underestimate of the true count. For the container separation of 8 cm, the two intervals ([104 111] and [102 108]) do not deviate too much from the ground count of 100. For canopy separations of 5, 7, and 9 cm, 3 out of 12 confidence intervals ([101 103], [101 101], [102, 102]) do not contain the ground truth data. However, the ground truth count is close to those confidence intervals.

In addition to interpreting the results by the confidence interval, the counting accuracy of the results was evaluated as well. The counting accuracy is calculated by Eq. (4-1) and Eq. (4-2).

\[
\text{Accuracy (i)} = \frac{|\text{average algorithm count}(i) - \text{ground count}(i)|}{\text{ground count}(i)} \tag{4-1}
\]

\[
\text{Overall Accuracy} = \frac{\sum_{i=1}^{n} \text{Accuracy}(i)}{n} \tag{4-2}
\]

where:

- n is the number of replications.
The counting accuracies of all available treatments are shown in Figure 4-9. The overall accuracy for container separations of 0 and 3 cm was above 78%, the accuracy for a container separation of 8 cm was above 92%, for container separations of 13, 18, and 23 cm, accuracies increase to 98%. Therefore, counting accuracy increased as container separation increased from 0 cm to 13 cm. There was no obvious trend of counting accuracy when the container separation increased from 13 cm to 23 cm. Counting accuracy was only decided by the distribution of canopy area since the canopies were not touching. The amount of container separation was not a key factor. In the case of 8 cm, where the canopy was touching but not overlapping, there was canopy interaction between adjacent plants. Thus, accuracy was not as good as when canopies were separated, but remains much higher than the case in which canopies are overlapped. When canopies are overlapped, in the case of container separations of 0 and 3 cm, an underestimation of plants occurs because the reference area is much larger than the canopy area of container plants in the severely compact region of interest. If the reference area is taken as basis and used for estimation, the count will be underestimated.

Since the count data is not complete at altitudes of 15 and 18 m with container separations of 0, 3, and 8 cm, it is not possible to give a conclusion on the effect of altitude on the accuracy. However, when container separation is 13, 18, and 23 cm, capturing images at 15 m would be optimal.

Considering the error source when container separation is 0 cm, one possible solution to correct the result is to adjust the arrangement of the training plants. Specifically, four (2 × 2) and nine (3 × 3) plants were placed with the same canopy
separation as the region of interest instead of a completely separate arrangement as in the original setting. The comparison between the counting accuracy and training area (in pixels) with the new training scheme and with the original setting are shown in Table 4-2.

From Table 4-2, no improvement was observed when using four squeezed plants and nine squeezed plants as training plants. The intention was to decrease the reference area by changing the training scheme. However, the reference area is a result of both the placing scheme and the plant variation itself. In other words, even four relatively large plants are placed in a squeezed way; the average area may be still larger than that of four relatively small plants. This explains why the reference area in the \((2 \times 2)\) and \((3 \times 3)\) settings were 20,572 pixels and 19,955 pixels compared to the reference area 18,579 pixels in the separate setting. Therefore, the decrease in average canopy area is a result of a large-scale squeezed block. Even though efforts were made to adjust the training plants to simulate the setting of the region of interest, several plants are still not enough.

### 4.3.1.2 Effect of Height, Canopy Interval, and Ground Cover for Fire Chief™ Arborvitae (*Thuja occidentalis* L.)

To evaluate the effects of different variables and their combinations on the counting accuracy, a three-way analysis of variance (ANOVA) was performed in JMP Pro 12. The effect tests are shown in Table 4-3. The spacing has an effect on the counting accuracy (Figure 4-10). A Tukey HSD test (Table 4-4) showed that accuracy at a spacing of -5 cm was significantly different from that of 0 and 5 cm. There was found to be no significant effect of heights on accuracy. It could be observed that the difference between the highest and lowest accuracy with different heights cannot
exceed 2% with a fixed canopy spacing. This indicated that image resolution is not a dominant factor on counting accuracy. Also, the background had no effect on accuracy. Although fabric background has a larger contrast with plants than gravel, the counting accuracy has no significance difference.

Background and spacing have an interaction effect on the accuracy that can be clearly seen in Table 4-5. For the black fabric background, the overall accuracy of Fire Chief™ arborvitae completely separated (canopy interval 5 cm) was higher than 97.8%, when touching (interval 0 cm) accuracy was approximately 94.2%, while the accuracy for overlapping canopy (interval -5 cm) was approximately 72.0% (Figure 4-11). This was consistent with the results reported in perennial peanut. For the gravel background, the accuracy for touching and separated canopies are 91.7% and 89.8%, while the accuracy for overlapping is 75.8% (Figure 4-12). The possible reason that the separated case fails to overweigh the touching case is that the poor segmentation between plants and the gravel background due is to the color similarity between plants and gravel. The interval space in the separated case between adjacent plants is a source of error.

Counting error is extremely high when arborvitae plants are severely overlapped (spacing of -5 cm) as also observed with perennial peanut. Calibration is needed in this case. Previous discussion illustrates that the effect of altitude is not significant. Therefore, calibration was performed on the counting results of all heights with a canopy spacing of -5 cm on black fabric. There are two ground counts, 56 and 64. A linear regression \( y = 0.5484x + 37.022, R^2 = 0.87 \) between the ground count and the algorithm count was built (Figure 4-13). The correlation between the two counts is approximately 0.91. To evaluate the counting accuracy after calibration, the regression
formula was applied to all automated counts and the calibrated counts were obtained. Error is calculated based on the calibrated counts and ground truth data. The calibrated counting accuracy is shown in Table 4-6. The average accuracy after calibration was 98.25% for -5 cm canopy separation.

Since all the counting results are based on the reference area, it is valuable to check the performance of the algorithm in one standard deviation range of the reference area. Interval counting was applied to each block with two other base areas:

mean (training areas) − stdv (training areas) and mean (training areas) + stdv (training areas).

This will provide a counting range [low, high]. Counting results based on reference area mean will be included as well. The results are shown in Table 4-7.

The results indicated that even the reference area was decreased by the standard deviation for sets with 5 cm canopy overlap; the total count number was still underestimated.

For sets with 0 cm and 5 cm canopy spacing, 25 of 36 (70%) ranges include the ground truth count. The [low, high] range could give the growers a rough inventory number. In Figure 4-14, average counting gaps (high-low) were listed in different heights and at different spacings. The average gap for sets with 0 cm canopy spacing is 11, while the average gap for sets with 5 cm and -5 cm canopy spacing are 5 and 10, respectively. The sets with touching canopies and overlapping canopies have more fluctuation with variation of reference area than a squeezed block. This is a result of erosion and dilation operations. For separate cases, the effect of the morphology operation is smaller compared to the touching and overlapping cases. It is clearly
observed that the counting gap at 12 m is minimal in all spacing cases. This indicates that the algorithm behaves more stable at 12 m when there is variation in the reference area.

4.3.2 Sparse Container Block

The sparse block contains 80, 60, 40, and 20 ground containers. The experiment was replicated four times within each condition. A 95% confidence interval of four algorithm counts was used to evaluate the accuracy of algorithm for each missing conditions. Results are listed in Table 4-8. A 95% confidence interval was reported for all count conditions, which indicates that the algorithm count is not significantly different from the ground count (p=0.05). From Table 4-8, we can see that 95% confidence intervals for all conditions contain the ground count which indicates that the algorithm count is not significantly different from the ground count (p=0.05).

To better observe the change of counting accuracy when the density of plants varied, the original 100-plant counting accuracy at 12 m spaced at 8 cm was also included. The counting accuracy for each condition is listed in Figure 4-15.

The overall trend shows that when more plants are removed from the block, higher accuracies will be obtained. The only exception is when there are 40 nursery containers remaining. The four replicated ground counts for this condition is 40, 40, 37, and 40. The relatively error resulting in low accuracy comes from the singular algorithm count of 37. The possible reason is that all the images were taken when the sky was sunny except for one with 37 counting results which were taken when the sky was a bit cloudy. The overall trend is a consequence of a more clearly defined canopy because more spacing results in less interaction between plants. The overall accuracy for all the missing case is higher than 96%. This indicates that the algorithm could be applied for
practical use when containerized plants are removed because of selling, shipping, or mortality.

4.3.3 Algorithm Generality

4.3.3.1 Effect of Canopy Shape and Effect of the Presence of Flowers

Each experiment included two runs. In each run, two treatments were replicated five times in a randomized block design. In total, there are 10 counting results for each treatment case, respectively. Table 4-9 and Table 4-10 shows the average counting accuracy for all the four treatments.

The accuracy for regular plants was 98.1% while the accuracy for irregular plants was 94.4%. This indicated that the algorithm performs better when the canopy shape is regular because the canopy area is a source of large variance when canopy shape is irregular. The counting algorithm is built based on the assumption that the variance of canopy area is small across our region of interest (ROI). The more variance the canopy area has, the less accurate the algorithm.

The accuracies for plants with flowers and plants without flowers were 96.9% and 97.7%, respectively. The results indicates the same SVM model together with interval counting scheme works well when the ROI and training plants are within the same category (plants with or without flowers). However, we are expected to have a mixed category of plants under real-world conditions. In the current experiment, the average canopy area for the plants with flowers is 20,478 pixels while that for the plants without flowers is 19,153 pixels. However, fields may exist that have mixed categories of plants under real-world conditions. The performance of the algorithm to mixed nurseries will need to be studied in the future. There is a slight difference of the canopy area between
these two categories. Additional research is needed to appropriately choose a training set for mixed block scenarios.

4.3.3.2 Commercial Nursery Field

The panoramic image (Figure. 4-16) was stitched in Microsoft ICE. The ground truth data was provided by an employee who went through the entire nursery field covered in the image. The ground count was 22,000 for the whole field, and the count for each plot is not available. The eight training plants are marked in the red rectangle. The algorithm count was 20889, an accuracy of approximately 95.0%. The algorithm proves to work well in the practical field with very low image resolution (7-10 cm).

The ground truth data is a great challenge. For this field, it took one employee nearly seven hours to complete the manual count. If the field were larger, the cost of labor will be much higher. Besides the cost of labor, accuracy is another limiting factor related to manual scouting. In this case, the employee worked for some time, took a rest, and then went back to work. How to get an accurate manual counting is very important for further development and validation of the counting algorithm.

4.4 Conclusions

A counting algorithm based on canopy area was built by assuming that there is a small variance between plant canopy areas. Canopy area was estimated in the binary image obtained through the classification method mentioned in the previous chapter. The developed algorithm was tested in different scenarios.

Two sets of experiments have been done to test the effect of height and canopy spacing on counting accuracy. The first experiment shows that the algorithm worked better when there was less overlapping between plants. However, the amount of the canopy spacing is does not really matter. Because the data was not complete due to
camera orientation deviation, it was difficult to make a conclusion on the effect of height. The accuracy for the extreme squeezed block is higher than 78% and for touching-canopy or separate-canopy block is higher than 92%. The second experiment also explored the effect of ground cover in addition to the effects of height and canopy spacing. A three-way ANOVA test (p=0.05) was performed which shows that spacing had effect on counting accuracy. In addition, spacing and background had an interaction effect on counting accuracy. For the fabric background, the results were similar to those of the first experiment, i.e. accuracy is approximately 71% for the overlapped case, 93% for the touching case, and 97% for the separated case. For gravel, the touching cases (92%) outperform the separates case (90%). The counting accuracy for the overlapped case on fabric after linear calibration is 98.47% compared to 75% before calibration.

The stability of the counting algorithm in one standard deviation range of reference area was also tested. The results shows that the counting results of the separated case have less variation regarding the fluctuation of the reference area compared to the touching and overlapped cases. The counting range obtained with the base areas mean (training areas) − stdv (training areas) and mean (training areas) + stdv (training areas) is useful in providing a rough estimate of the inventory data.

The random sparse blocks with 100, 80, 60, 40, and 20 container nurseries were created. The accuracies for all the cases were higher than 94%. The overall trend shows the smaller the density, the higher the counting accuracy. This is very practical when the density is changing with shipping, moving, selling, or mortality.

The counting accuracy is compared for irregular shaped and regular shaped plants, and plants with and without flowers. Results show that the counting accuracy for
regular plants (98.13%) is higher than that of irregular plants (94.38%), and the counting accuracy for plants without flowers (97.66%) is higher than that of plants with flowers (96.88%). This proves that the counting scheme could work for different shapes and different growing stages.

The algorithm was applied to a commercial field which contained a 22 000 container nursery. The automatic count is 20,889, representing a counting accuracy of approximately 95%. This is a real production area and the grower’s expected counting accuracy is about 90%. The results prove that the algorithm works in a real nursery field.
Table 4-1. 95% confidence intervals for four automated counts for each treatment for perennial peanut.

<table>
<thead>
<tr>
<th>Canopy separation (cm)</th>
<th>Flight altitude (m)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9</td>
<td>12</td>
</tr>
<tr>
<td>0</td>
<td>82,87</td>
<td>78,79</td>
</tr>
<tr>
<td>3</td>
<td>84,91</td>
<td>73,86</td>
</tr>
<tr>
<td>8</td>
<td>104,111</td>
<td>102,108</td>
</tr>
<tr>
<td>13</td>
<td>100,102</td>
<td>98,101</td>
</tr>
<tr>
<td>18</td>
<td>99,101</td>
<td>101,103</td>
</tr>
<tr>
<td>23</td>
<td>99,101</td>
<td>101,101</td>
</tr>
</tbody>
</table>

Table 4-2. Counting accuracy and reference area (in pixels) with different training schemes.

<table>
<thead>
<tr>
<th>Training Scheme</th>
<th>Altitude (m)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Reference area</td>
<td>Accuracy</td>
</tr>
<tr>
<td>4 separated plants</td>
<td>18579</td>
<td>84.5%</td>
</tr>
<tr>
<td>4 plants with 0 cm interval</td>
<td>20572</td>
<td>76.5%</td>
</tr>
<tr>
<td>9 plants with 0 cm interval</td>
<td>19955</td>
<td>78.5%</td>
</tr>
</tbody>
</table>

Table 4-3. Three-way ANOVA with interaction for mean counting accuracy in response to spacing, height, and background for arborvitae.

<table>
<thead>
<tr>
<th>Source</th>
<th>Nparm</th>
<th>DF</th>
<th>Sum of squares</th>
<th>F ratio</th>
<th>Prob &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spacing</td>
<td>2</td>
<td>2</td>
<td>0.91065809</td>
<td>131.2511</td>
<td>&lt;0.0001*</td>
</tr>
<tr>
<td>Height</td>
<td>1</td>
<td>1</td>
<td>0.00069151</td>
<td>0.1993</td>
<td>0.6563</td>
</tr>
<tr>
<td>Spacing*Height</td>
<td>2</td>
<td>2</td>
<td>0.00013938</td>
<td>0.0201</td>
<td>0.9801</td>
</tr>
<tr>
<td>Background</td>
<td>1</td>
<td>1</td>
<td>0.01320468</td>
<td>3.8063</td>
<td>0.0540</td>
</tr>
<tr>
<td>Spacing*Background</td>
<td>2</td>
<td>2</td>
<td>0.06337147</td>
<td>9.1336</td>
<td>0.0002*</td>
</tr>
<tr>
<td>Height*Background</td>
<td>1</td>
<td>1</td>
<td>0.00077128</td>
<td>0.2223</td>
<td>0.6383</td>
</tr>
<tr>
<td>Spacing<em>Height</em>Background</td>
<td>2</td>
<td>2</td>
<td>0.00002379</td>
<td>0.0034</td>
<td>0.9966</td>
</tr>
</tbody>
</table>

Table 4-4. Tukey HSD test of effect of spacing on counting accuracy.

<table>
<thead>
<tr>
<th>Level</th>
<th>Least square mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>A</td>
</tr>
<tr>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>-5</td>
<td>B</td>
</tr>
</tbody>
</table>

*Means with the same letter are not significantly different based on Tukey HSD test (Q=2.38, p=0.05).
Table 4-5. Tukey HSD test of spacing and background on counting accuracy.

<table>
<thead>
<tr>
<th>Level</th>
<th>Least square mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>5, Fabric</td>
<td>A</td>
</tr>
<tr>
<td>0, Fabric</td>
<td>A</td>
</tr>
<tr>
<td>0, Gravel</td>
<td>B</td>
</tr>
<tr>
<td>5, Gravel</td>
<td>B</td>
</tr>
<tr>
<td>-5, Gravel</td>
<td>C</td>
</tr>
<tr>
<td>-5, Fabric</td>
<td>C</td>
</tr>
</tbody>
</table>

* Means with the same letter are not significantly different based on Tukey HSD test (Q=2.91, p=0.05).

Table 4-6. Calibrated accuracy for block spacing at -5 cm.

<table>
<thead>
<tr>
<th>Algorithm counts</th>
<th>Calibrated counts</th>
<th>Ground truth</th>
<th>Calibrated accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>43</td>
<td>61</td>
<td>64</td>
<td>94.69%</td>
</tr>
<tr>
<td>47</td>
<td>63</td>
<td>64</td>
<td>98.12%</td>
</tr>
<tr>
<td>47</td>
<td>63</td>
<td>64</td>
<td>98.12%</td>
</tr>
<tr>
<td>48</td>
<td>63</td>
<td>64</td>
<td>98.98%</td>
</tr>
<tr>
<td>46</td>
<td>62</td>
<td>64</td>
<td>97.26%</td>
</tr>
<tr>
<td>47</td>
<td>63</td>
<td>64</td>
<td>98.12%</td>
</tr>
<tr>
<td>51</td>
<td>65</td>
<td>64</td>
<td>98.45%</td>
</tr>
<tr>
<td>52</td>
<td>66</td>
<td>64</td>
<td>97.60%</td>
</tr>
<tr>
<td>50</td>
<td>64</td>
<td>64</td>
<td>99.31%</td>
</tr>
<tr>
<td>51</td>
<td>65</td>
<td>64</td>
<td>98.45%</td>
</tr>
<tr>
<td>50</td>
<td>64</td>
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<td>99.31%</td>
</tr>
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<td>65</td>
<td>64</td>
<td>98.45%</td>
</tr>
<tr>
<td>39</td>
<td>58</td>
<td>56</td>
<td>95.70%</td>
</tr>
<tr>
<td>36</td>
<td>57</td>
<td>56</td>
<td>98.64%</td>
</tr>
<tr>
<td>35</td>
<td>56</td>
<td>56</td>
<td>99.61%</td>
</tr>
<tr>
<td>36</td>
<td>57</td>
<td>56</td>
<td>98.64%</td>
</tr>
<tr>
<td>35</td>
<td>56</td>
<td>56</td>
<td>99.61%</td>
</tr>
<tr>
<td>34</td>
<td>56</td>
<td>56</td>
<td>99.41%</td>
</tr>
</tbody>
</table>
Table 4-7. Counting results on the shift of the reference area.

<table>
<thead>
<tr>
<th>Run #</th>
<th>Spacing</th>
<th>6 m Low</th>
<th>6 m High</th>
<th>6 m Mean</th>
<th>12 m Low</th>
<th>12 m High</th>
<th>12 m Mean</th>
<th>22 m Low</th>
<th>22 m High</th>
<th>22 m Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>RUN 1</td>
<td>0</td>
<td>61</td>
<td>69</td>
<td>64</td>
<td>61</td>
<td>68</td>
<td>64</td>
<td>60</td>
<td>66</td>
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### Table 4-8. 95% confidence interval of four algorithm counts for each missing condition.

<table>
<thead>
<tr>
<th>Ground count after missing</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>75,80</td>
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<tr>
<td>60</td>
<td>59,62</td>
</tr>
<tr>
<td>40</td>
<td>37,42</td>
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<tr>
<td>20</td>
<td>20,20</td>
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</tbody>
</table>

### Table 4-9. Counting accuracy for regular and irregular plants.

<table>
<thead>
<tr>
<th>Plant type</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>'Plumosa Compacta' (regular)</td>
<td>98.13%</td>
</tr>
<tr>
<td>'Sea Green' (irregular)</td>
<td>94.38%</td>
</tr>
</tbody>
</table>

### Table 4-10. Counting accuracy for plants with and without flowers.

<table>
<thead>
<tr>
<th>Plant type</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rose with flowers</td>
<td>96.88%</td>
</tr>
<tr>
<td>Rose without flowers</td>
<td>97.66%</td>
</tr>
</tbody>
</table>
Figure 4-1. Articulated boom used as a platform to collect images of container peanuts. (Photo courtesy of Ying She).
Figure 4-2. Aerial image of the experimental layout for container arborvitae. (Photo courtesy of Ying She).

Figure 4-4. Distribution of ground canopy area of arborvitae.
Figure 4-5. Distribution of canopy area in the image for arborvitae. A) At 6 m; B) At 12 m; C) At 22 m – run 1 and D) At 22 m – run 2.
Figure 4-5. Continued.
Figure 4-6. Boxplot of mean and standard deviation of canopy area in the image for regular and irregular Juniperus.

Figure 4-7. Boxplot of mean and standard deviation of canopy area in the image for plants with and without flowers.
Figure 4-8. Flowchart of interval counting.
Figure 4-9. Counting accuracy for perennial peanut (Arachis glabrata) with different container spacing and at different capturing height.

Figure 4-10. Least square mean plot of accuracy with different background and canopy spacing.
Figure 4-11. Counting accuracy for Fire Chief™ arborvitae (*Thuja occidentalis* L.) on black fabric with different canopy spacing and at different capturing heights.

Figure 4-12. Counting accuracy for Fire Chief™ arborvitae (*Thuja occidentalis* L.) on gravel with different canopy spacing and at different capturing heights.
Figure 4-13. Linear regression between algorithm counts and ground counts with spacing -5 cm.

Figure 4-14. Counting gap (high-low) according to shift of reference area.
Figure 4-15. Counting accuracy for different sparse blocks.
Figure 4-16. Stitched image of a commercial nursery field.
CHAPTER 5
DESIGN AND STABILITY OF COUNTING METHODOLOGY FOR CITRUS TREES

5.1 Background

Research in the area of tree inventory is broad and is divided into four main areas: species (Gentry, 1988; Williams-Linera, 2002), physical parameter estimates including size, diameter, and height (Næsset and Bjerknes, 2001; Popescu et al., 2003), health conditions (Sepulcre-Cantó et al., 2006; Sankaran and Ehsani, 2013), and total number of trees. This work, which falls into the latter area, targets citrus tree count estimation. Inventory management is a basic need in the citrus industry and is critical for appropriate management practices. For large citrus groves, manual counting is time-consuming and prone to errors. Since it is labor intensive for scouts to go through the large groves, the inventory information recorded by them may not be accurate. The estimate of the number of bearing citrus trees is very important in forecasting fruit counting. An accurate estimate of fruit counting could help growers to choose the best harvest time according to the market price in order to maximize their profit. Moreover, Brazil and the United States are highly competitive in the European and Asian citrus markets. The strategy of pricing citrus is partially based on the crop yield (Bohac, 2005). Having a more accurate estimate of citrus tree count would have a positive economic impact on the Florida citrus industry.

Remote sensing provides the capability to conduct inventory management with less dependence on human factors and cover a large area in a short time. The fastest growing remote sensing technology is Unmanned Aerial Vehicles (UAVs). It is expected that agriculture will be the largest market for UAVs in the next ten years (AUVSI, 2013).
Once the Federal Aviation Administration (FAA) allows the commercial use of UAVs in agriculture, one of the applications of UAVs is inventory management.

Another possible application for UAVs is to monitor crop health in orchards and nurseries. Trees could be identified and geo-referenced by UAVs to generate a tree-count map. Using this map, growers would be able to clearly highlight areas that show a decrease in tree count or density. A clear decrease in tree density in a given area would alert growers that there is a problem in the grove related to an abiotic or biotic stress that should be further investigated.

There are two types of remote sensing technology used for tree identification and counting: Light Detection and Ranging (LiDAR) and visible aerial images. LiDAR, also known as laser scanning, cannot directly be visualized without further processing. Jang et al. (2008) used airborne LiDAR data to retrieve the raster height image of apple orchards, and then applied the local maximum to detect treetops. Treetop detection via local maximum was also included in other research work with LiDAR or laser data (Viau et al., 2005; Yu et al., 2011; Oliveira et al., 2012; Zhang et al., 2015). Alternatively, visible aerial images, the second type of remote sensing technology have been used to identify and count trees. Similar to finding the local peak of a tree via LiDAR data, local maxima of images were used to locate the tree crown (Pitkänen, 2001; Pouliot et al., 2002; Wang et al., 2004; Larsen et al., 2011; Srestasathier and Rakwatin, 2014).

Karantzalos and Argiales (2004) used an anisotropic diffusion filter and local spatial maximum of the Laplacian to detect well-spaced, non-overlapping olive trees. However, Kaartinen et al. (2012) pointed out that few of the tree detection methods are able to achieve the accuracy required by tree counting. Besides treetop detection, Suárez et al.
(2003, 2005) investigated the use of eCognition to count trees based on an object-based classification using aerial photography. However, the software requires numerous parameter settings in order to obtain a satisfactory classification results.

There are three reasons which make it difficult to apply the above technology to citrus inventory management in Florida: 1) all citrus trees are flat topped to reduce the cost of harvesting and spraying, which makes it impossible to identify individual trees with local maximum technology. 2) Since treetop information is not available, splitting the touching and overlapping trees would be a huge challenge in the estimation of tree count. If no proper splitting mechanism is applied, the tree count will be underestimated. 3) Most inventory systems were designed for forests which have a dense canopy and no shadows. However, shadows are a great challenge for image segmentation in agriculture (Guo et al., 2013; Lu et al., 2013; Teimouri et al., 2014). Shadows occurring inter-row or within row may result in unsuccessful identification of plants. Although flights are usually scheduled at noon to avoid the shadow problem, exploring a method to remove the shadows could make the flight time more flexible.

The objectives of this research are: 1) to find a classification method which could be used for extracting citrus trees when shadows are present inter-row or between-row; 2) to develop an interactive and user-friendly counting method which would function when individual tree detection algorithms would fail due to tree topping and the canopy of adjacent trees are touching and overlapped.
5.2 Materials and Methods

5.2.1 Image Collection

A Cessna 172 airplane was used for image collection on 30 November, 2014 at Immokalee, FL, USA (26.44736, -81.09343). The total area of the citrus grove was approximately 34.8 acres. The airplane flew at 95-112 knots at 2,500 feet and 3,500 feet and used an on-board camera, i.e., a Canon EOS 5D Mark III (Canon Inc., Tokyo, Japan). The camera was a 22.3 megapixel full-frame infrared-enabled camera that was modified to include red, green, and near infrared (NIR) bands. Images collected at the same altitude were stitched by Pix4D.

5.2.2 Graph Cut Application for Image Segmentation

Many problems in computer vision can be described as an energy minimization problem. In an image, assume \( L = \{L_1, L_2, \ldots, L_p\} \) is a vector which specifies the labels of each pixel. For a two-class classification problem, \( L_i \) can be only “background” or “object”. The energy function of an image can be expressed in Eq. (5-1).

\[
E(L) = \lambda \cdot R(L) + B(L)
\]  

(5-1)

where \( R(L) \) is the region term, \( B(L) \) is the boundary term and \( \lambda \) is a regulation parameter which controls the importance of the region and boundary terms. Specifically, the region term and the boundary term are expressed in Eq. (5-2) and Eq. (5-3), respectively.

\[
R(A) = \sum_{p \in P} R_p(L_p)
\]  

(5-2)

\[
B(A) = \sum_{(p,q) \in N} B(p,q) \cdot \delta(L_p, L_q); \quad \delta(L_p, L_q) = \begin{cases} 1 & \text{if } L_p \neq L_q \\ 0 & \text{otherwise.} \end{cases}
\]  

(5-3)
where \( R_p(L_p) \) is the penalty for assigning pixel \( p \) to label \( L_p \) and \( B(p, q) \) defines the penalty for the discontinuity of \( p \) and \( q \). Normally, the more similar two pixels, the larger \( B(p, q) \). The basic idea for graph cut is to construct a weighted graph such that the minimum cut on the graph also leads to the minimization of the energy function. A weighted graph is represented by \( G = \{V, E\} \). \( V \) consists of nodes for each unclassified pixel and two nodes for terminal pixels, represented as \( S \) and \( T \). \( E \) contains all the edges connecting pairs of nodes. There are two types of links in a graph: a terminal link (t-link) which connects a terminal node and a regular node, and a neighborhood link (n-link) which connects two regular nodes. The illustration of the graph is shown in Figure 5-1.

Our goal is to find the minimal cut that segments two terminal nodes into two subgraphs. The cost of the cut is defined as the sum of weights the cut serves. An example for edge weights set is shown in Eq. (5-4) to Eq. (5-6).

\[
\begin{align*}
    w(p, S) &= R_p("background") = -\ln Pr(I_p\mid"background") \\
    w(p, T) &= R_p("object") = -\ln Pr(I_p\mid"object") \\
    w(p, q) &= B(p, q) = \exp\left(-\frac{(l_p - l_q)^2}{2\sigma^2}\right)
\end{align*}
\]

Matlab Wrapper (Bagon, 2006) of Graph Cut Version 1.1 (Boykov et al., 2001; Kolmogorov and Zabih, 2004; Boykov and Kolmogorov, 2004) was used in this study. The parameters settings for the GraphCut interface are as follows:

DataCost is defined as the negative log likelihood of the pixel belonging to each cluster according to its RGB value. We first applied k-means to perform a two-class rough segmentation and obtain two clusters. DataCost can be expressed as Eq. (5-7).
\[ D_i(c) = -\log(\mathcal{N}(I_i|\mu_c, \Sigma_c)) = (I_i - \mu_c)^T \Sigma_c^{-1}((I_i - \mu_c)) \] (5-7)

where \( I_i \) is the feature vector of pixel \( i \), \( \mu_c \) is the centroid locations of cluster \( c \), and \( \Sigma_c \) is the covariance matrix of cluster \( c \).

SmoothnessCost is a number of labels by number of labels matrix where \( SC(label_1, label_2) \) represents the cost of assigning neighboring pixels with \( label_1 \) and \( label_2 \). It is spatially invariant. In this study, all diagonal elements are set to 0, and all other elements are set to 10.

\([vC, hC]\) is the vertical and horizontal spatially variant smoothness cost. In this study, they are set as the vertical and horizontal gradients of the original image filtered by a Gaussian filter.

5.2.3 Vegetation Detection Based on Vegetation Index Thresholding

The green normalized difference vegetation index (GNDVI) is a measure of green vegetation. The GNDVI equation (Gitelson et al., 1996) was derived by differential reflectance at a near infrared band and a green band as shown in Eq. (5-8).

\[ GNDVI = \frac{NIR - G}{NIR + G} \] (5-8)

Two-thousand pixels of plants, shadows, and background are chosen, respectively; a histogram of each category is shown in Figure 5-2. From the histogram, it can be seen that the shadow pixels interfere with the plant pixels. If the shadow is removed beforehand, the GNDVI can be used to extract plants from the background.

5.2.4 Counting Scheme

Although most trees are planted at the same time, there are still some newly planted trees. For newly planted trees, they have not yet begun to touch the neighboring
trees, and their canopy area is smaller than that of mature trees. Based on the segmentation results, an area threshold (T) was set. If the canopy area is smaller than T, it is counted as one tree. It is assumed that the total number found in this range is \( Count_{small} \). After all the small trees and single trees are removed, the assumption is that the block with the canopy area larger than T is connected trees. Since they were planted at the same time, the diameters and canopy areas are expected to have a small variance. Three different counting models were used for counting citrus trees as described in the following sections.

5.2.4.1 Count Based on Canopy Area (CBA)

In container inventory management, an interval counting method was proposed to conduct the counting task. In order to obtain the canopy area, some training plants were intentionally placed outside the region of interest. In the citrus production industry, the algorithm was trained based on segmentation results. The detailed process is shown as below:

(1) Randomly choose a segmented connected citrus tree row and count all pixel number in that row (P). Manually count the tree number in that row (T);

(2) Calculate the reference area \( \left( \frac{P}{T} \right) \) for interval counting;

(3) Apply interval counting to the grove and get counting results \( Count_{interval} \);

(4) Calculate the total count \( (Count_{interval} + Count_{small}) \)

5.2.4.2 Count Based on Constant Planting Length (CBL)

In citrus production, the planting interval between trees is grove-dependent. However, the interval is constant within each grove. A tree row of the remaining connected blocks is randomly chosen, and the length L (in pixels) of the major axis of
the ellipse that has the same normalized second central moments as the region is recorded. The major axis is parallel to tree row direction. Then, manually counting is used to determine the tree number (N) in the selected row. The interval d will be \( \frac{L}{N} \). An example of the tree row length calculation is shown in Figure 5-3. There are three resultant blobs after segmentation. The lengths on the major axis are \( d_1 \), \( d_2 \), and \( d_3 \). In this case, total tree count will be the summation of \( \frac{d_1 + d_2 + d_3}{d} \) and \( Count_{small} \).

5.2.4.3 Count Based on Projection (CBP)

Projection (vertical, horizontal, radial, etc.) provides the feature distribution in the projection direction. In image processing, projection is often applied on binary images. Tang et al. (2016) used vertical projection on binary images to detect the center line of crop rows. To measure leaf length, An (2015) executed a radial scan from plant center on binary images to yield a curve. The peaks on the curve are assumed to be leaf tips.

In this work, citrus rows were projected vertically. Instead of binary images, masked GNDVI images were used. Figure 5-4 and Figure 5-5 gave an example of a marked GNDVI image and projection curve of a citrus row (the values of the curve are averages of the GNDVI value in the projected direction). Before finding the accurate peaks, the curve was smoothed using a Savitzky-Golay filter to remove the effect of the rough edges of the citrus trees. Peaks were found by locating the zeros of first derivatives of the smoothed curve. In the space where trees were missing, the weeds could also contribute to the curve. However, due to the size and random growing direction of the weeds, it is unlikely that the projected value is large enough compared to the tree. In order to eliminate the effects of weeds, peaks with a magnitude lower than 0.07 were excluded. Furthermore, to capture the most intense signal of trees, the
tallest peaks within a certain distance ("block distance") were chosen and all other peaks were ignored. It is expected that the block distance should be close to planting space. However, to make sure that the algorithm does not miss any peak, the “block distance” is set smaller than the planting interval.

Table 5-1 lists the reference area for CBA, tree interval for CBA, and block distance for CBP (in pixels) used in this work.

5.2.5 Ground Truth Data

Citrus groves are usually large. Manual scouting takes a lot of time. Moreover, the accuracy of manual counting cannot be guaranteed if a worker works non-stop. As an alternative to manual scouting, a digital counter pen 3133 (Control Co.) was used to determine the ground counts on the printed image. Each time a black mark was made with the pen, a beep sound rings and the count on LCD display automatically increased by 1. Since the citrus trees are connected with each other and sometimes it is hard to identify single trees, three different persons did the manual counting and the average number was taken as the ground truth.

5.2.6 Performance Evaluation

To evaluate the performance of the proposed work, count results from the proposed method were compared with ground count data. Since the developed algorithm is a number-oriented method instead of a detection-oriented method, the performance is measured via counting accuracies defined by Eq. (5-9). In addition, the correlation ($R^2$) between the automated count and the manual count was measured.

$$\text{Accuracy} = 1 - \frac{|\text{Algorithm count} - \text{Ground Count}|}{\text{Ground Count}} \tag{5-9}$$
5.3 Results and Discussion

The original image and segmentation results generated by the graph cut are shown in Figure 5-4 A and Figure 5-4 B. The image is segmented into a light purple region and a dark purple region in the labeled image Figure 5-4 B. The light purple region includes the shadow area and the ditch area between citrus grove sections, and it serves as a mask to remove the unwanted shadow and ditches.

Although graph cut successfully removed shadows, the citrus trees are still not separated from the road and other background features. Based on the histogram of the GNVDI of plants and other backgrounds (Figure 5-2), the threshold was set at 0.2 to extract the canopy area from other backgrounds. Figure 5-4 C shows the binary segmentation result after the GNDVI threshold was applied. Most non-canopy areas are removed; however, some small isolated non-canopy regions still exist. Morphological operation (erosion after dilation) was applied to Figure 5-4 C, and the final segmentation result is shown in Figure 5-4 D.

For CBA, an area threshold k was applied to remove the young (small) trees from the connected trees on the binary images, and the number of small trees was recorded. Figure 5-5 provided an example of marked small and connected trees. Those isolated smaller trees were successfully identified. Area variation for the left connected region will be smaller than that of the whole region. Applying area mapping on the left region will be more stable.

Figure 5-6 showed the original image, the GNDVI gray image of a masked tree row, the vertical projection curve, and the final identified tree locations. It is clear to see that the curve could capture the outline of the tree row and the final locations almost coincident with the points where the tree diameter vertically projects.
Based on the setting parameters, CBA, CBL, and CBP were applied, and the three algorithm count results were compared with the manual count. The number of trees detected by the algorithms, manually count number, and counting accuracy at 2,500 feet and 3,500 feet are presented in Table 5-2 and Table 5-3.

From Table 5-2, the overall accuracy for CBA, CBL, and CBP is 96.0%, 95.5%, and 96.8%, respectively. Overall, CBP has the highest counting accuracy. For CBL, the overall accuracy and average accuracy are almost the same because all counting results are overestimated. For CBA and CBP, both underestimation and overestimation exist. Therefore, the overall accuracy is higher than the average accuracy due to the compromise between underestimation and overestimation.

From Table 5-3, the overall accuracy for CBL (97.4%) and CBP (99.5%) are much higher than that of CBA (86.8%). For CBA at 3,500 feet, there are two sections whose accuracies are only approximately 0.65. This is because a large variation in canopy area exists in these sections which makes estimating counts by area less accurate. Similar to the case at 2,500 feet, the overall accuracy is higher than average accuracy.

Based on the average accuracy, it can be concluded that CBL and CBP are more accurate than CBA at both 2.500 feet and 3,500 feet. This is because citrus trees are planted at a nearly constant distance. For CBA, it is hypothesized that the canopy area does not differ too much within the grove. However, variation in the canopy area still exists. Accuracies at 2,500 feet are higher than those at 3,500 feet, which indicates that the proposed method works better when image resolution is higher.
Correlation curves for 2,500 feet are shown in Figure 5-7 A–C; those for 3,500 feet are shown in Figure 5-8 A–C. At 2,500 feet, the correlation coefficient between the manual count and CBA is 0.988, between the manual count and CBL is 0.998 and between the manual count and CBP is 0.992. The corresponding correlation coefficients are 0.905 (CBA), 0.975 (CBL), and 0.955 (CBL) at 3,500 feet. At both altitudes, CBL and CBP outperformed CBA in terms of correlation, which is the similar to the results of counting accuracy. The foundation of CBL and CBP is planting interval which is more uniform compared to the canopy area, which served as foundation for CBA. All correlation coefficients at 2,500 feet are higher than those at 3,500 feet. The higher the image resolution, the higher the correlation coefficient.

5.4 Conclusions

Citrus tree counting is very critical for management purposes and yield estimation. In this paper, three methods were proposed and compared for citrus tree inventory management by using modified color images which enables the NIR band. The hypothesis of the three proposed methods is that canopy area within the grove does not deviate significantly and the citrus planting interval is constant.

Tree canopy extraction was performed via graph cut theory and GNDVI threshold. A graph cut algorithm based on maximum flow/min cut was applied to classify shadow and non-shadow regions in order to mask shadow regions. Then, the threshold of GNDVI was set at 0.2 to extract the vegetation region from the vegetation and non-vegetation mixed regions.

Compared to the conventional tree detection method which relies on local peaks, the key advantages of the three methods presented in this work are 1) they could be
applied when trees are topped and do not have local peaks; 2) they provide solutions for overlapping splitting.

The proposed methods were tested on stitch images collected at 2,500 feet and 3,500 feet. The performance of the proposed methods was evaluated using counting accuracy and the correlation coefficient. Average counting accuracies are 94.4% (CBA), 95.7% (CBL), and 95.1% (CBP) at 2,500 feet and 83.2% (CBA), 95.1% (CBL), and 93.1% (CBP) at 3,500 feet. The correlation between the CBA and ground count is 0.988 at 2,500 feet and 0.905 at 3,500 feet, between CBL and ground count is 0.998 at 2,500 feet and 0.975 at 3,500 feet, between CBP ground count is 0.992 at 2,500 feet and 0.955 at 3,500 feet. CBL is the most accurate method, CBA is the worst. Both CBL and CBP were developed based on planting spacing, which is more stable than the canopy area which is the foundation of CBA. Image resolution is another factor. The higher the altitude, the lower the accuracy. However, growers may expect to cover more fields in a short time, so a higher altitude may be preferable. The citrus counting process is a tradeoff between the area of covered fields in a fixed time and accuracy.

Usually, there is strong relationship between the canopy diameter and the age of the tree. Therefore, canopy diameter will be retrieved from the ages of the trees to a diameter mapping database, and canopy area could be calculated based on the diameter. Through flight height, field-of-view, and resolution of the sensor, pixel size can be obtained. Then, canopy area of the image (in pixels) can be calculated based on ground canopy area and pixel size. The planting interval in the image can be calculated based on planting spacing and pixel size. Therefore, this technology can be applied to
different groves if the ages of the tree, flight height, field-of-view, and resolution of the sensor can be provided by the growers.
Table 5-1. Corresponding area and spacing threshold for different heights.

<table>
<thead>
<tr>
<th>Flying altitude (ft)</th>
<th>Area (pixels)</th>
<th>Length (pixels)</th>
<th>Minimum distance (pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2,500</td>
<td>2600</td>
<td>45</td>
<td>30</td>
</tr>
<tr>
<td>3,500</td>
<td>1150</td>
<td>35</td>
<td>25</td>
</tr>
</tbody>
</table>

Table 5-2. Counting results for images taken at 2,500 feet.

<table>
<thead>
<tr>
<th>Ground count</th>
<th>CBA</th>
<th>Accuracy</th>
<th>CBL</th>
<th>Accuracy</th>
<th>CBP</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>169</td>
<td>165</td>
<td>97.6%</td>
<td>177</td>
<td>95.3%</td>
<td>168</td>
<td>99.4%</td>
</tr>
<tr>
<td>208</td>
<td>214</td>
<td>97.1%</td>
<td>220</td>
<td>94.2%</td>
<td>219</td>
<td>94.7%</td>
</tr>
<tr>
<td>230</td>
<td>219</td>
<td>95.2%</td>
<td>241</td>
<td>95.2%</td>
<td>240</td>
<td>95.7%</td>
</tr>
<tr>
<td>209</td>
<td>196</td>
<td>93.8%</td>
<td>214</td>
<td>97.6%</td>
<td>198</td>
<td>94.7%</td>
</tr>
<tr>
<td>146</td>
<td>129</td>
<td>88.4%</td>
<td>148</td>
<td>98.6%</td>
<td>152</td>
<td>95.9%</td>
</tr>
<tr>
<td>86</td>
<td>80</td>
<td>93.0%</td>
<td>91</td>
<td>94.2%</td>
<td>83</td>
<td>96.5%</td>
</tr>
<tr>
<td>108</td>
<td>93</td>
<td>86.1%</td>
<td>111</td>
<td>97.2%</td>
<td>100</td>
<td>92.6%</td>
</tr>
<tr>
<td>105</td>
<td>105</td>
<td>100.0%</td>
<td>112</td>
<td>93.3%</td>
<td>109</td>
<td>96.2%</td>
</tr>
<tr>
<td>110</td>
<td>102</td>
<td>92.7%</td>
<td>115</td>
<td>95.5%</td>
<td>116</td>
<td>94.5%</td>
</tr>
<tr>
<td>318</td>
<td>297</td>
<td>93.4%</td>
<td>334</td>
<td>95.0%</td>
<td>341</td>
<td>92.8%</td>
</tr>
<tr>
<td>320</td>
<td>328</td>
<td>97.5%</td>
<td>343</td>
<td>92.8%</td>
<td>340</td>
<td>93.8%</td>
</tr>
<tr>
<td>209</td>
<td>203</td>
<td>97.1%</td>
<td>214</td>
<td>97.6%</td>
<td>217</td>
<td>96.2%</td>
</tr>
<tr>
<td>182</td>
<td>174</td>
<td>95.6%</td>
<td>187</td>
<td>97.3%</td>
<td>193</td>
<td>94.0%</td>
</tr>
<tr>
<td>Overall</td>
<td>2400</td>
<td>2305</td>
<td>96.0%</td>
<td>2507</td>
<td>95.5%</td>
<td>2476</td>
</tr>
<tr>
<td>Average</td>
<td>94.4%</td>
<td>95.7%</td>
<td>95.1%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5-3. Counting results for images taken at 3,500 feet.

<table>
<thead>
<tr>
<th>Ground count</th>
<th>CBA</th>
<th>Accuracy</th>
<th>CBL</th>
<th>Accuracy</th>
<th>CBP</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>62</td>
<td>96.7%</td>
<td>60</td>
<td>100.0%</td>
<td>58</td>
<td>96.7%</td>
</tr>
<tr>
<td>191</td>
<td>203</td>
<td>93.7%</td>
<td>172</td>
<td>90.1%</td>
<td>200</td>
<td>95.3%</td>
</tr>
<tr>
<td>198</td>
<td>191</td>
<td>96.5%</td>
<td>178</td>
<td>89.9%</td>
<td>180</td>
<td>90.9%</td>
</tr>
<tr>
<td>88</td>
<td>104</td>
<td>81.8%</td>
<td>88</td>
<td>100.0%</td>
<td>85</td>
<td>96.6%</td>
</tr>
<tr>
<td>118</td>
<td>144</td>
<td>78.0%</td>
<td>130</td>
<td>89.8%</td>
<td>142</td>
<td>79.7%</td>
</tr>
<tr>
<td>43</td>
<td>58</td>
<td>65.1%</td>
<td>41</td>
<td>95.3%</td>
<td>45</td>
<td>95.3%</td>
</tr>
<tr>
<td>88</td>
<td>110</td>
<td>75.0%</td>
<td>89</td>
<td>98.9%</td>
<td>78</td>
<td>88.6%</td>
</tr>
<tr>
<td>147</td>
<td>135</td>
<td>91.8%</td>
<td>140</td>
<td>95.2%</td>
<td>137</td>
<td>93.2%</td>
</tr>
<tr>
<td>139</td>
<td>171</td>
<td>77.0%</td>
<td>142</td>
<td>97.8%</td>
<td>135</td>
<td>97.1%</td>
</tr>
<tr>
<td>126</td>
<td>137</td>
<td>91.3%</td>
<td>135</td>
<td>92.9%</td>
<td>120</td>
<td>95.2%</td>
</tr>
<tr>
<td>112</td>
<td>137</td>
<td>77.7%</td>
<td>114</td>
<td>98.2%</td>
<td>104</td>
<td>92.9%</td>
</tr>
<tr>
<td>201</td>
<td>223</td>
<td>89.1%</td>
<td>185</td>
<td>92.0%</td>
<td>216</td>
<td>92.5%</td>
</tr>
<tr>
<td>197</td>
<td>259</td>
<td>68.5%</td>
<td>189</td>
<td>95.9%</td>
<td>217</td>
<td>89.8%</td>
</tr>
<tr>
<td>Overall</td>
<td>1708</td>
<td>1934</td>
<td>86.8%</td>
<td>1663</td>
<td>97.4%</td>
<td>1717</td>
</tr>
<tr>
<td>Average</td>
<td>83.2%</td>
<td>95.1%</td>
<td>93.1%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 5-1. Graph illustration. Boykov, Y. Y. and Jolly, M. P. 2001. Interactive graph cuts for optimal boundary and region segmentation of objects in N-dimensional (ND) images.

Figure 5-2. Histogram of GNDVI for plants, shadows, and background.
Figure 5-3. Calculation of length on major axis.

Figure 5-4. An example of citrus image processing. A) Original image; B) Labeled image after graph cut; C) Image after thresholding; D) Image after erosion and dilation.
Figure 5-5. An example of small and connected trees separation. A) Marked small trees; B) Marked connected trees.
Figure 5-6. An example of CBP. A) Original image; B) Masked GNDVI image; C) Vertical projection of GNDVI image; D) Peak detection result.
Figure 5-7. Regression between manual and algorithm count at 2,500 ft. A) Automated count by area information; B) Automated count by spacing information; C) Automated count by projection.
Figure 5-8. Regression between manual and algorithm count at 3,500 ft. A) Automated count by area information; B) Automated count by spacing information; C) Automated count by projection.
CHAPTER 6
CONCLUSIONS AND FUTURE WORK

Color images were obtained for the purpose of counting plant inventory in an open field container nursery. Three species (peanut, arborvitae, and rose) with popular colors (green, yellow, and flowering) on fabric background were chosen for segmentation purpose. Segmentation methods were aimed at dealing with the color differences of the plants. For red and green plants, index thresholding was applied. For flowering plants, support vector machine (SVM) was used for classification. False positive and false negative rates were calculated to evaluate segmentation results which were based on index thresholding. It showed that few plant pixels were classified as background pixels. However, background pixels were never classified as plants pixels. The evaluation of an SVM classifier was based on the LIBSVM package. The overall segmentation accuracy for the three plant species was higher than 97%. The segmentation methods were documented for further nursery segmentation with similar colors.

The distribution of the canopy area fitted a Gaussian distribution. Therefore, a counting scheme was built based on canopy area mapping. The base area was calculated via training plants. A counting algorithm was tested in one standard deviation range of the base area to check the stability of the algorithm regarding the fluctuation of the reference area. The result shows that the counting results of separate cases have less variation compared to the touching and overlapped cases. In addition, the counting range obtained with the mean of the two base areas (training canopy areas) - stdv (training canopy areas) and mean (training canopy areas) + stdv (training canopy areas) is useful to give a rough estimate of the inventory data.
The developed algorithm was tested on different scenarios, and the effects of different factors on the counting accuracies were tested. It showed that the sparser the nursery block, the more accurate the counting. The effects of image resolution, canopy spacing and ground cover were also evaluated. Results showed that spacing and interaction between spacing and background had some effect on counting accuracy. Overall, more spacing between neighboring containers will lead to higher counting accuracy. Since the algorithm is based on area mapping, it will not perform well when severe overlap exists. Different calibration methods (calibration on training area and calibration on counting results) were used in this work. A linear calibration on counting results showed promising results. The algorithm was proven to be applicable to regular plants (98.13%), irregular plants (94.38%), plants with flowers (96.88%), and plants without flowers (97.66%).

Modified color images were obtained for citrus counting purposes. Graph cut was used for tree segmentation. Considering the limitation of the traditional tree detection method on citrus tree counting, three different counting methods (counting based on canopy area (CBA), counting based on constant planting length (CBL), and counting based on projection (CBP)) were developed based on assumption of the tree canopy area and planting spacing. CBA was the canopy mapping method in nursery counting, and CBL and CBP were based on planting spacing. Results showed that CBL and CBP have higher counting accuracy and correlations with manual counts than CBA. This indicates that in citrus orchards, there is a lot of variation in canopy area. To test the effect of image resolution, aerial images were obtained at 2,500 feet and 3,500 feet. The overall accuracy is above 95.5% and 86.8%, respectively, which indicates that
higher image resolution will lead to higher counting accuracy. The correlation coefficients between manual count and automated count for three methods are higher than 0.99 and 0.91 at 2,500 feet and 3,500 feet, respectively.

Future work should be focused on evaluating the algorithm under different light conditions and on mixed category fields. Making a commercial product based on the developed algorithm that allows growers customize the parameters based on their needs could be another focus.
LIST OF REFERENCES


algorithm. In 2006 IEEE Southwest Symposium on Image Analysis and Interpretation (pp. 61-65). IEEE.


BIOGRAPHICAL SKETCH

Ying She was born in Chongqing, China. She received her bachelor’s degree in electrical engineering from China Agricultural University (CAU) in 2011. In the same year, she came to the University of Florida to start her Ph.D. program in Department of Agricultural and Biological Engineering and she received her Ph.D. in the summer of 2016. She also received her master’s degree in computer engineering at the University of Florida in 2014.