Fusion of LIDAR Data and High Resolution Images for Forest Canopy Modeling

Liang-Chien Chen, Tsai-Wei Chiang, Tee-Ann Teo
Center for Space and Remote Sensing Research,
National Central University
Jhong-Li, TAIWAN.
lcchen@csrsr.ncu.edu.tw, {93322084, 92342016}@cc.ncu.edu.tw

Abstract: Three-dimensional forest model is important to forest ecosystem management. Traditional ground investigation requires vast amount of manpower, resources, costs, and time. Hence, it is difficult to promptly obtain accurate information by using ground investigation. Nowadays, Light Detection And Ranging (LIDAR) technology provides high density 3-D point clouds. It can rapidly obtain 3-D information of forest structure. On the other hand, the high resolution images provide plentiful spectral information of forest coverage. Thus, we propose here a scheme to merge LIDAR data and high resolution images for the reconstruction of forest canopies. The objective of this investigation is to perform 3-D forest canopy modeling using LIDAR data and high resolutions image. The proposed scheme comprises three major steps: (1) data preprocessing, (2) vegetation detection, and (3) tree crown extraction. In the vegetation detection, a region-based segmentation and knowledge-based classification are integrated to detect tree regions. Then, a watershed segmentation is performed to extract each individual tree. The LIDAR data used in this research are obtained by Optech ALTM and Leica ALS40 systems. The average density of LIDAR data is about 1.7 points per square meter. The aerial photos with 1:5,000 scale are used in this investigation. Preliminary results indicate that the proposed scheme may reach reliable results.
Key Words: LIDAR, High Resolution Image, Forest Model.

1. Introduction

Remote sensing technology has been applied to forest ecosystem management for many years. Internationally, there have been important scientific advances in remote sensing over the last 30 years that have produced mature techniques ready for implementation in the management of forest resource. Most of the researches utilize the spectral characteristics of optical images to detect the forest and delineate the independent tree crown [1][2]. However, optical images are easily influenced by topographical covers and weather condition. In addition, the ability of optical images in piercing through the forest area is not good enough, so it cannot capture the forest structure directly. Previous studies used high resolution digital images to estimate tree heights, canopy density, forest volume, and biomass [3]. A trial study by Næsset [4] revealed that automated softcopy photogrametric method did not provide better results when compared to manual photogrammetric techniques for estimating tree heights [4]. Nowadays, LIDAR technology provides horizontal and vertical information at high spatial resolution and vertical accuracies. Forest attributes such as canopy height can be directly retrieved form LIDAR data. A review of the rapidly growing literature on LIDAR applications emphasize needs for data fusion in the processing phase of LIDAR data as a method to improve various feature extraction task. Therefore, we integrate LIDAR data and high resolution image to build up the forest canopy model.

The strategy of individual tree extraction can be divided into the following methods: (1) Pixel-based method [5], (2) Region-based method [6], (3) Contour-based method [6], and (4) Empirical method (Forest parameter method) [8][9]. In the pixel-based approach, like watershed segmentation, it applies mathematical morphology to explore the geometric structure of trees in an image. The advantages of this approach are that the method may selectively preserve structural information while accomplishing desired tasks on the image. In the region-based approach, homogeneity regarding the shape and color in the neighborhood is examined in a region growing process. The contour-based approach minimizes the internal energy by weighting the parameters. In the empirical method (Forest parameter method), it uses large amount of the ground truth to derive forest parameters like tree crown width, tree height, age and various property of tree. Then, a mathematical model is built to find the relationships among them. A typical example is that the tree height and tree crown width have the linear relationship through the regression analysis.

The objective of this investigation is to perform 3-D forest canopy modeling using LIDAR data and high resolution images. The proposed scheme comprises three major steps: (1) data preprocessing, (2) vegetation detection, and (3) tree crown extraction. The data preprocessing includes space registration of LIDAR and high resolution images, derivation of above ground surface from LIDAR data, and generation of spectral index from high resolution images. In the vegetation detection, a region-based segmentation followed by the knowledge-based classification is employed to detect tree regions. In the next step, we perform the tree crown extraction in vegetation regions. We use watershed segmentation and local maximum search to extract tree crowns. Fig.1 shows the flowchart of the proposed method.

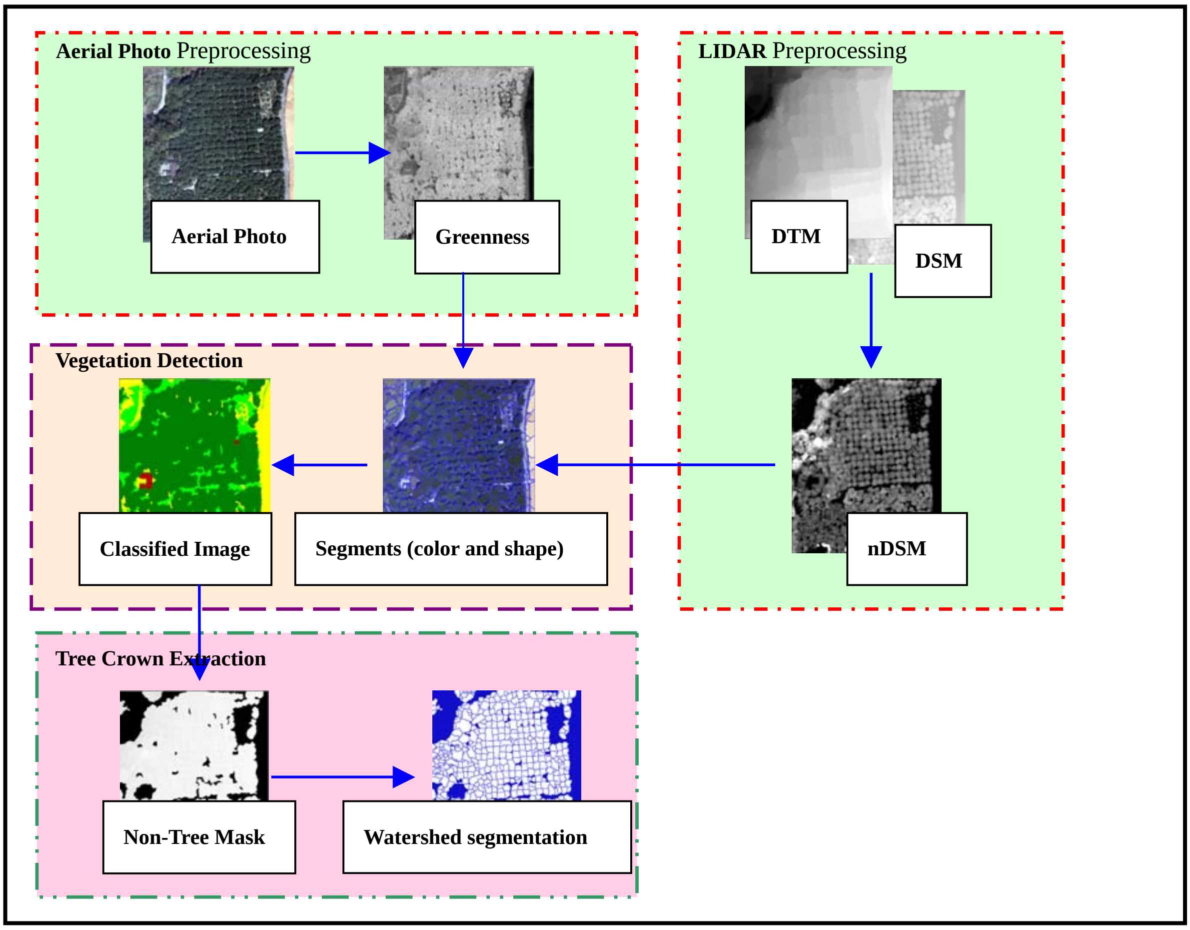


Fig. 1. Flowchart of the proposed method

2. Methodology

The proposed scheme includes three parts: (1) data preprocessing, (2) vegetation detection, and (3) tree crown extraction. The preprocessing includes geometric and radiometric processing. Then a divided-and-conquer strategy is incorporated to detect the vegetation followed by tree crown extraction.

1) Data Preprocessing

The preprocessing includes three major works: (1) space registration, (2) derivation of above ground surface, and (3) generation of spectral index. The LIDAR data is used to generate Digital Terrain Model (DTM) and Digital Surface Model (DSM) in grid form. In the space registration, the images are orthorectified using the DSM and the ground control points. The rectified images are essentially co-registered with the LIDAR data. We subtract the DTM from DSM to generate the normalized DSM (nDSM). In which, the nDSM represents the above ground surface that is used to separate the ground and above ground objects. We use red and green bands to calculate the greenness index [10]. Eq. (1) shows the formula of greenness index. The greenness index is majorly used in identifying the vegetation areas.

$$\text{Greenness} = (G-R) / (G+R) \qquad (1)$$

2) Vegetation Detection

The objective of vegetation detection is to extract the vegetation areas, so that the non-vegetation areas would not interfere the tree crown extraction in the following step. We integrate the region-based segmentation and knowledge-based classification in this stage. We combine elevation from LIDAR data and radiometric features from orthoimages in the segmentation. Thus, the pixels with similar height and spectral attributes are merged into a region. After the segmentation, each separated region is a candidate object for classification considering the height and spectral characteristics. Finally, the vegetation areas are extracted by a fuzzy logic classification.

We first use a multiple data segmentation technique to perform region-based segmentation. It can identify objects with correlated characteristics in terms of reflectance and height. In this step, we fuse the nDSM and the greenness derived from aerial photo for segmentation. This method identifies geographical feature using scale homogeneity parameters obtained from the spectral reflectance in RGB and the elevation value in the nDSM. Homogeneity is described by a mutually exclusive interaction between color and shape. Eq. (2) shows the formula of the homogeneity index. The homogeneity index is composed based on spectral and shape factor. It considers the spectral and shape information simultaneously. The formulas of color and shape factor are show in Eq. (3) and Eq. (4). The weights of color and shape factor should be set properly. The color factor uses the standard deviation of the region as a segmentation criterion. Shape factors select the smoothness and compactness of region boundary for weighting. The formulas for the calculations of smoothness and compactness are shown in Eq. (5) and Eq. (6), respectively.

After the segmentation, we use the object-oriented classification in vegetation detection. The classification is based on a fuzzy logic classification system where the membership functions employ thresholds and weights for each data layer. The above ground and high greenness objects are classified as vegetation.

$$H = w * h_{color} + (1-w) * h_{shape} \quad (2)$$

where,

H: homogeneity index,
h_{color}: spectral factor,
h_{shape}: shape factor, and
w: weighting for spectral and shape factor.

$$h_{color} = \sum w_c * \sigma_c \quad (3)$$

where,

$h_{color:}$ spectral factor,
Wc: weighting among layers, and
σ_c: standard deviation of pixel value in a region.

$$h_{shape} = w_s * h_{smooth} + (1-w_s) * h_{compact} \quad (4)$$
$$h_{smooth} = \mathbf{L / B} \quad (5)$$
$$h_{compact} = \mathbf{L / N^{0.5}} \quad (6)$$

where,

$h_{shape;}$ shape factor, and
w_s: weighting for smoothness and compactness,
h_{smooth}: smoothness of region,
$h_{compact}$: compactness of region,
L: border length of region,
B: shortest border length of region,
N: area of region.

3) Tree Crown Extraction

After the vegetation detection, we focus on the vegetation areas for the extraction of tree crowns. The work includes three major parts: (1) segmentation of LIDAR data, (2) local maximum search and (3) extraction of forest parameters. Fig.2 shows the flowchart of the tree crown extraction. First, we apply watershed segmentation method on DSM [5]. It can find the changes of individual tree height, so we can extract the boundary of each individual tree. We assume that the maximum point in the boundary is the tree position. Local maximum filter is applied to extract the tree position, as shown in Fig.2, where the symbol of ” ” represents the determined location. The forest parameters for each tree crown include tree position and height.

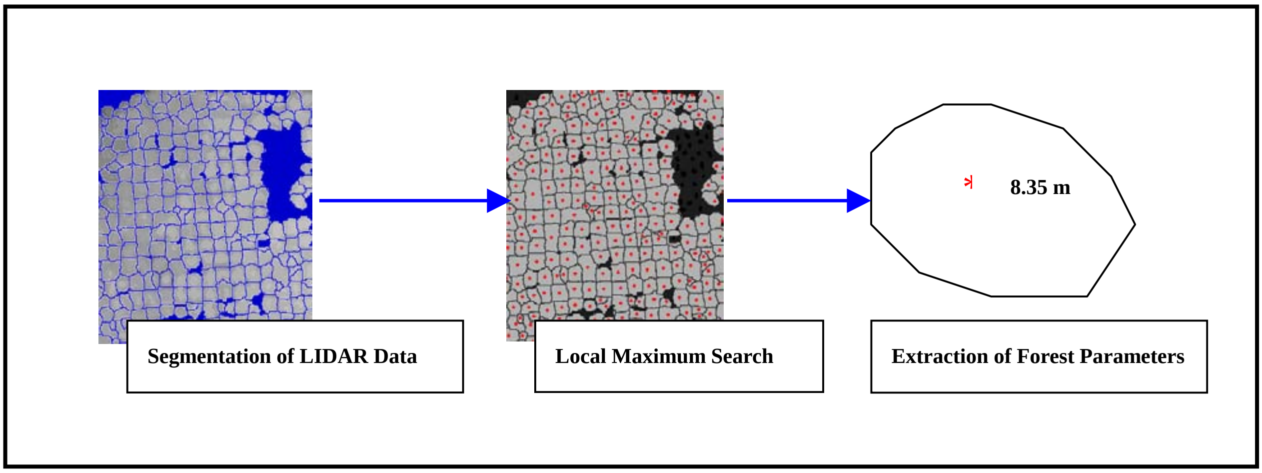


Fig. 2. Flowchart of the tree crown extraction

3. Experiment Results

There are two test sites in this validation, one is in an urban area and another is an orchard place. The urban area is located in Hsin-Chu city. The LIDAR data was obtained by using Leica ALS40. The average density of LIDAR data is about 1.7 points per square meter. The vertical accuracy is about 0.15 m. The second test area is located near Tai-Chung city that is characterized by an orchard. The LIDAR data used in the area was obtained by using Optech ALTM2033. The average density of LIDAR data is about 1.6 points per square meter. The vertical accuracy is also about 0.15 m. Table 1 shows the parameters of the LIDAR data sets in the two test sites.

Color aerial photos with a scale of 1:5,000 are used in this investigation. Scanned with 20µm pixel spacing ,the ground resolution of the digital images is about 10 cm. Table 2 shows the parameters of the aerial photos in the test areas.

Table 1. LIDAR data set.

LIDAR		
Case	Hsin-Chu	Tai-Chung
Sensor	ALS40	ALTM2033
Acquire Date	2002.04.14	2002.03.20
Flying height(m)	1200-2000	1350-1500
Density (pts/m2)	1.6	1.7

Table 2. Aerial photo data set.

Aerial Photo		
Case	Hsin-Chu	Tai-Chung
Acquire Date	2002.05.14	2002.06.19
Focal length(mm)	305.110	304.926
Flying height(m)	1543.43	1595.18
Ground resolution(cm)	10	10

In the region-based segmentation, we first set the weights of the image layers on homogeneity segmentation using a commercial package, i.e. eCognition. Table 3 shows the parameters in the homogeneity segmentation. The weighting of LIDAR part and aerial photo is 2:1. Considering the shape of the forest is irregular, the color factor is more important than the shape factor. Hence, the color and shape factors are 0.8 and 0.2, respectively. After segmentation, we perform the object-oriented classification to determine the tree regions. We use the extracted tree regions in the individual trees extraction. Assuming that the highest point in the boundary is a treetop, one segmented boundary is selected to represent one tree crown. Finally, we use stereoscopic viewing to measure tree heights and tree crowns as the references for validations.

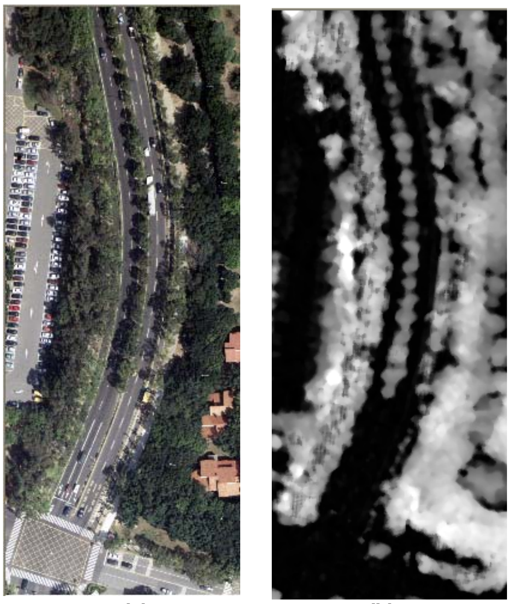
Table 3. Parameters in the homogeneity segmentation.

Weight		Homogeneity parameter				
LIDAR	Aerial photo	Scale	Color	Shape	Smoothness	Compactness
0.67	0.33	10	0.8	0.2	0.8	0.2

1) Hsin-Chu Case

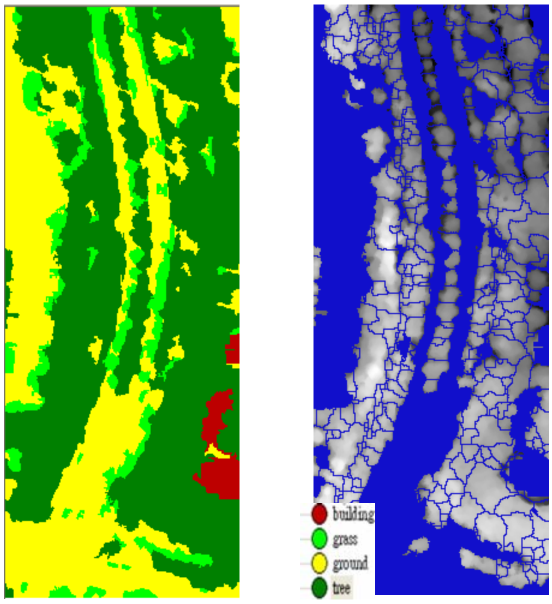
In Hsin-Chu case, we identify objects with correlated characteristics in terms of reflectance and height. Fig. 3a is the aerial photo and Fig. 3b is the nDSM. After the vegetation detection, we use tree areas to perform watershed segmentation on the DSM. Fig. 4a shows the classification results. Fig. 4b is the block results, which are derived from the watershed segmentation. The background image is the corresponding DSM.

Then we check each segmentation boundary for examining the reliability of tree crown determination. If they are matched, we compare the elevation for accuracy assessment. In this case, we have 22 trees in the reference data. The number of detected trees is 25. The correctness is, thus, 88%. Fig. 7a shows the locations for those trees. Then, we use those 22 matched boundaries to determine the local maximum height for the analysis of the accuracy. The RMSE is 0.46 m. The error histogram is shown in Fig. 8a.



(a) (b)

Fig. 3. Data description. (a) aerial photo of Hsin-Chu case, (b) nDSM of Hsin-Chu case

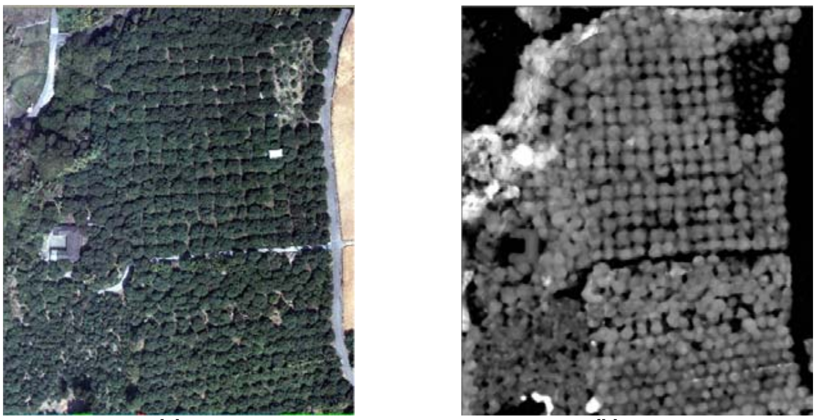


(a) (b)

Fig. 4. Segmentation results. (a) classification result of Hsin-Chu case, (b) individual tree extraction result of Hsin-Chu case

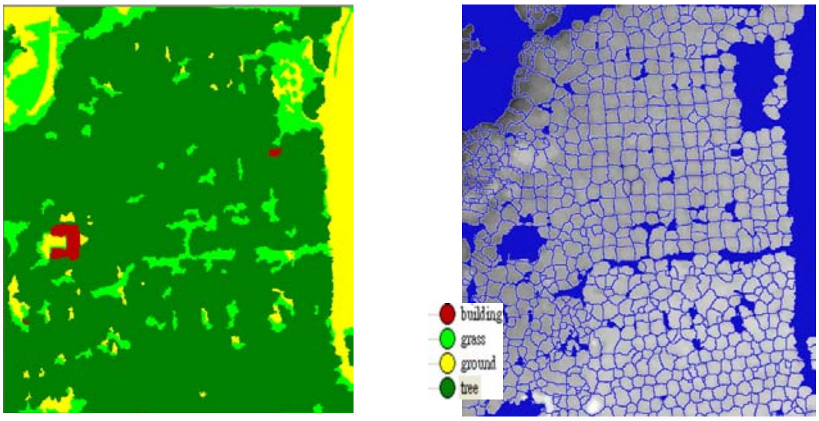
2) Tai-Chung Case

Fig. 5a is the aerial photo used in the Tai-Chung case. Fig. 5b is the nDSM. Fig. 6a illustrates the classification results. Fig. 6b is the block results from watershed segmentation, which are overlapped on the DSM. Then we check each segmentation boundary for examining the reliability of tree crown determination. In this case, we have 197 trees in the reference data. The number of detected trees is 210. The correctness is, thus, 94%. Fig. 7b shows the locations for those trees. Then, we use those 197 match boundaries to determine the local maximum height for the analysis of the accuracy. The RMSE is 0.62 m. The error histogram is shown in Fig. 8b.



(a) (b)

Fig. 5. Data description. (a) aerial photo of Tai-Chung case, (b) nDSM of Tai-Chung case

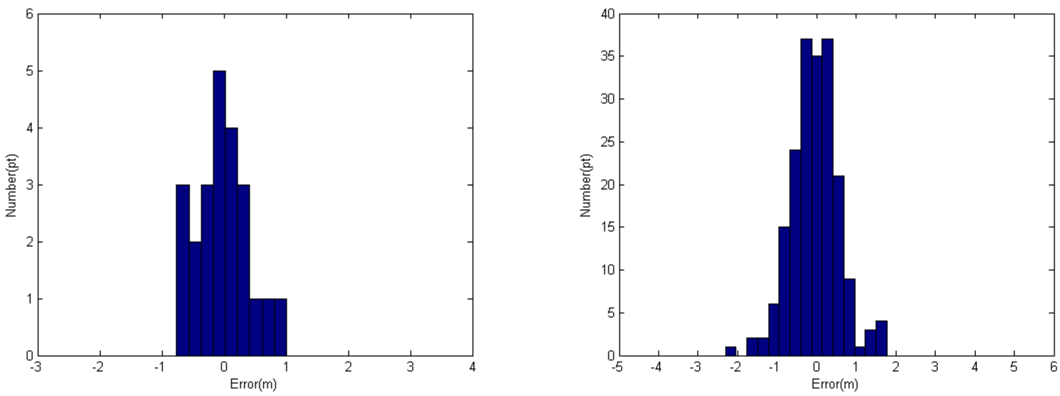


(a) (b)

Fig. 6. Segmentation results. (a) classification result of Tai-Chung case, (b) individual tree extraction result of Tai-Chung case

(a) (b)

Fig. 7. Ground truth. (a) Hsin-Chu case, (b) Tai-Chung case



(a) (b)

Fig. 8. Error histogram. (a) Hsin-Chu case, (b) Tai-Chung case

4. Conclusions

We have presented a scheme of forest modeling by the fusion of spectral and height information. The preliminary results indicate that the correctness of the canopy extraction reaches 88% and the accuracy of extracted tree heights is better than 0.62m. Considering the errors in the photogrammetric measurements for reference data set, the accuracy could be under estimated. The results show that the proposed scheme may be used to estimate tree height on individual tree level. The inclusion of digital aerial images with NIR bands is suggested and will be included in the future work.

Acknowledgement

This investigation was partially supported by the Remote Sensing Group of the Council of Agriculture under Project No. 93AS-2.5.1-ST-a2. The authors would like to thank the Council for providing the test data sets.

References

[1] Gong, P., Mei, X., Biging, G.S. and Zhang, Z., 2002. Improvement of an oak canopy model extracted from digital photogrammetry. Photogrammetric Engineering and Remote Sensing, 63(9): 919-924.

[2] Wang, L., Gong, P., and Biging, G.S., 2004. Individual Tree-Crown Delineation and Treetop Detection in High-Spatial-Resolution Aerial Imagery. Photogrammetric Engineering and Remote Sensing, 70(3): 351-357.

[3] Sheng, Y., Gong, P., and Biging, G.S., 2003. Model-Based Conifer canopy Surface Reconstruction form Photographic Imagery : Overcoming the Occlusion, Foreshortening, and Edge Effects. Photogrammetric Engineering and Remote Sensing, 69(3):249-258.

[4] Næsset, E., 2002. Determination of mean tree height of forest stands by digital photogrammetry. Remote Sensing of Environment, (78):328-340.

[5] Yu, X., Hyyppä, J., Kaartinen, H., and Maltamo, M., 2004. Automatic detection of harvested tees and determination of forest growth using airborne laser scanning. Remote Sensing of Environment, (90):451-462.

[6] Suárez, J.C., Ontiveros,C., Smith, S., and Snape, S., 2005. Use of airborne LiDAR and aerial photography in the estimation of individualtree height in forestry. Computer and Geosciences, (31):253-262

[7] Persson, A., Holmgren, J., and Soderman, U., 2002. Detecting and measuring Individual trees using an airborne laser scanner, Photogrametry Engineering and Remote Sensing, 68(9):925-932.

[8] Popescu, S.C., Wynne, R..H., 2004. Seeing the trees in the forest: using LIDAR and multispectral data fusion with local filtering and variable window size for estimating tree height. Photogrametry Engineering and Remote Sensing, 70(5):589-604.

[9] Riaño, D., Chuvieco, E., Condés, S., and Ustin, S.L., 2004. Generation of crown bulk density for Pinus sylvestris L. from lidar. Remote Sensing of Environment, (92) 345-352.

[10] Niederöst, M., 2001, Automated update of building information in maps using medium-scale imagery (1:15,000), Institute of Geodesy and Photogrammetry. Automatic Extraction of Man-Made Objects from Aerial and Space Images, (3):161-170.

[11] Definiens Imaging, 2004. eCoginition User’s Guide. http://www.definiens-imaging.com.