A STUDY OF SUBTROPICAL FOREST STRUCTURE USING HIGH DENSITY AIRBORNE LIDAR DATA

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ABSTRACT: Airborne lidar system is becoming an effective tool for tree crown identification and canopy mapping. This study involves the examination of tree position depicted by digital surface model and canopy height model derived from lidar point cloud of a subtropical forest. Due to the complex structure of the forest, little of the lidar point arrives at the ground. It is expected that the lidar point data density has significant effect on the accuracy of tree position determined from the point data. To verify this, a lidar data with an averaged point density of 276 points/m^2 was obtained and the point density was randomly thinned to 1, 5, 10, 20, 30, 40, 50, and 100 points/m^2. The results of the tree positions were compared to that using a FARO Photon 120 terrestrial laser scanner.

1. INTRODUCTION

The information of forest structural parameters is important for forest resource management. Recent studies have been carried out on identification of individual tree crowns and biophysical characteristics of coniferous forest using airborne laser scanning (ALS), or airborne lidar, and terrestrial laser scanning (TLS) (Puttonen, *et al*., 2010; Forzieri, *et al*., 2009). It is established that laser scanning technology offers a cost-effect way to extract tree position and height. However, few studies have been done on deriving structural parameters in deciduous forest. In this work, the canopy height model for a deciduous forest is derived from high density ALS data and used for the study of forest structural parameters.

2. MATERIALS AND METHODS

2.1 Study Area and ALS Data

The study area is located near the Nan-Shih River, north Taiwan, with the latitude and longitude of 24°54’00” and 121°33’20”, respectively (Figure 1a.). It is a subtropical forest with an area of 18.5 ha., characterized by deciduous trees and few coniferous stands. The mean elevation is 128 m, with the maximum and minimum elevations being 220 m and 70 m, respectively. The study area was scanned by an Optech ALTM 3070 system, operated at an above ground height of 500 m in May 2009. This study area is choosing a part of region to measure and process the tree position, the mean point density of the lidar data is 276 points/m^2 and the point density map is shown in Figure 1b.

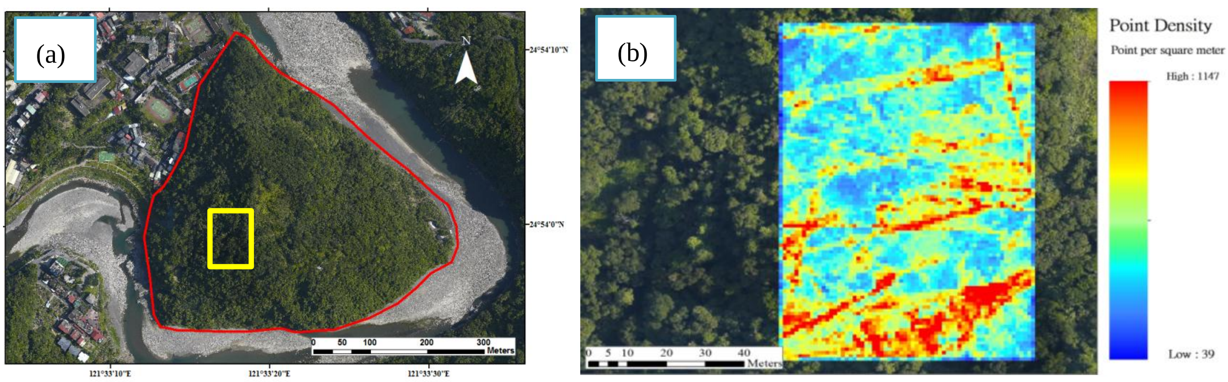

Figure 1. (a) the rectangle indicates the study area and (b) point density map of the study area.

2.2 Tree Position Extraction of ALS

For each cell, the highest lidar point is being selected form digital surface model (DSM). Due to the dense canopy, the lowest lidar point is not necessarily the representation of the digital elevation model (DEM) for each cell (Figure 2). Therefore, the ground points are selected manually and the DEM is interpolated to each cell. The CHM is then generated by subtracting DEM from DSM (Popescu and Wynne, 2004a; Popescu, *et al*., 2004b).

In this study, we are making a different number of point densities to process the DSM, DEM and CHM. Use the random sampling method for thinning ALS Lidar data to 1, 5, 10, 20, 30, 40, 50 and 100 points/meter^2.

Most tree-top detective methods are application the local maximum moving-window filter (Hyyppä and Inkinen, 1999; Suarez, *et al*., 2005). This filter assesses if the cell at the center of the window has the highest value and accepts it only if true (Barilotti, *et al*., 2007; Pirotti, 2010). The kernel size is relating the crown size (Wulder, *et al*., 2000); therefore, we are choosing the 4m kernel size for local maximum moving-window filter and it is an average distance between trees.

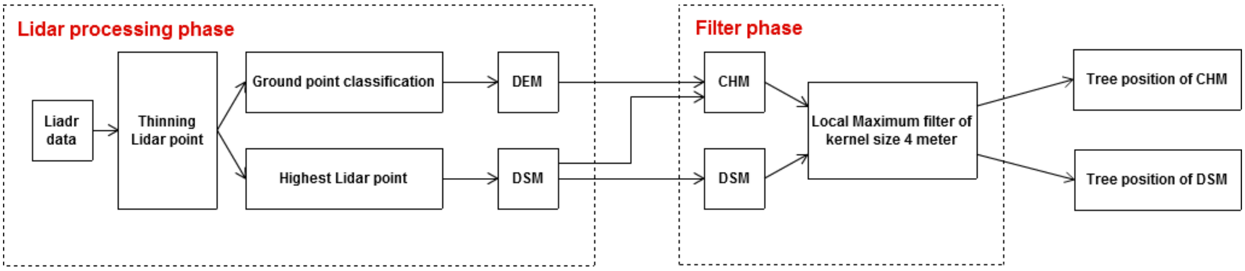

Figure 2. procedure of filter application in its two phases.

2.3 Field Survey and Ground Truth Values

The objective of this study was to estimate ground truth positions from point clouds scanned by a terrestrial laser scanner over a dense forest where the tape measure cannot obtain enough tree position accurate. Moved the 6 scan stations and the 70m×20m sample area was being chosen in the study area, and point clouds were then collected by utilizing FARO Laser Scanner Photon 120 laser scanner in May 25 2011. The e-GPS was survey the ground control point, which the Photon 120 was measured the tree position, height and diameter breast height (D.B.H) from post-processing.

First, we were extraction the terrestrial lidar data to 0.1m thickness from 1.3 to 1.4 m height upper the ground. The extracted lidar data could find out many circles and it was the stem profiles, for each circle, we used the circle fit method to detect the D.B.H and tree position parameters (Figure 3.). Finally, the tree height was subtracting the maximum from minimum point’s elevation at radius 2m of tree position.

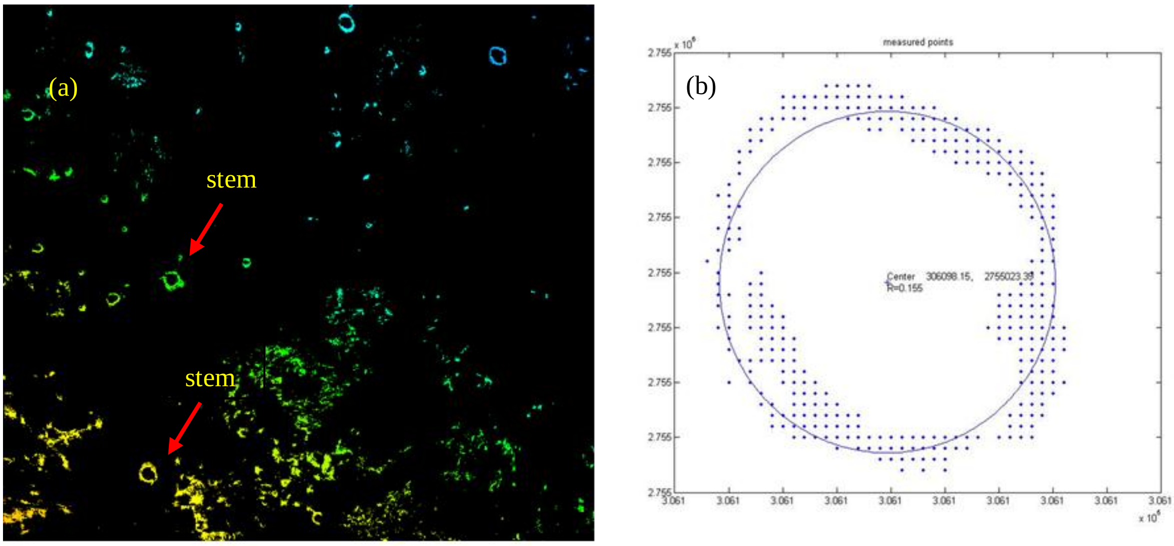

Figure 3. (a) stem profiles and (b) stem circle fitting

In this study, 34 tree positions were detected from terrestrial laser scanner, which the 34 trees include the dominant tree and overtopped tree, and therefore need classification the tree structures into two parts, because DSM and CHM methods all of used the surface point data for extracting the tree position, and the DSM and CHM were effective in detecting the dominant trees, in other words, the overtopped tree will be becoming an omission error. The terrestrial laser scanner detected tree position include 27 dominant trees and 7 overtopped trees (Table 1.), we selected the dominant trees to evaluate the quantifying error, which shows that the average distance between trees in those areas is 4.0 meters (Figure 4.).

Figure 4. ground truth positions of 27 trees

Table 1. the valus of ground truth positions

ID	East (m)	North (m)	DBH (cm)	Height (m)	ID	East (m)	North (m)	DBH (cm)	Height (m)
0	306053.73	2754823.28	18.16	16.32	14	306062.66	2754786.77	24.02	13.98
1	306053.22	2754820.23	15.40	12.07	15	306062.03	2754790.94	25.20	14.29
2	306064.37	2754816.37	26.84	16.15	16	306065.17	2754792.34	25.14	14.17
3	306052.46	2754816.46	28.12	11.10	17	306053.83	2754814.78	24.68	11.73
4	306054.43	2754808.46	23.68	11.97	18	306065.82	2754769.17	11.88	10.00
5	306061.97	2754797.72	21.74	13.26	19	306062.80	2754783.03	32.34	13.61
6	306056.20	2754799.53	8.24	11.60	20	306055.88	2754791.87	26.56	14.54
7	306055.72	2754794.19	27.48	14.28	21	306058.21	2754769.95	19.76	11.12
8	306061.59	2754779.81	34.36	13.05	22	306065.58	2754808.92	16.26	11.72
9	306061.86	2754773.84	23.80	10.78	23	306056.07	2754788.82	35.60	13.19
10	306059.15	2754766.26	27.88	11.33	24	306053.29	2754771.00	40.80	9.24
11	306055.13	2754776.31	15.10	8.92	25	306058.32	2754763.44	42.10	9.68
12	306068.03	2754761.02	7.00	17.09	26	306055.58	2754800.76	32.46	11.44
13	306063.29	2754789.52	23.24	14.19					

*East and North are TWD97 coordinate system

2.4 Error Assessment

Cohen and Fleiss have proposed different applications for the coefficient of agreement, respectively for categorized items and for categorical ratings in a number of class items. This study case considers reliability of crown-top position correspondence to position of trunk at breast height. These two elements can have a spatial offset, thus the objective is not to estimate absolute position error, but to estimate agreement in tree detection considering expected chance agreement together with omission and commission errors.

$$Pr_a = \frac{N_m}{N_s}$$

$$C_{err} = \frac{N_c}{N_m + N_c + N_o}$$

$$O_{err} = \frac{N_o}{N_m + N_c + N_o}$$

$$Pr_e = C_{err}^2 + O_{err}^2$$

$$\kappa = \frac{Pr_a - Pr_e}{1 - Pr_e}$$

where Pr_a is observed agreement and Pr_e is chance agreement, N_m is number of matching points, N_s is number of surveyed points, N_c is number of points assigned as commission errors, and N_o is number of points assigned as omission errors. κ values are plotted as a function of correlation; Percentage of tree extraction is the ratio of matched to surveyed tree ratio: N_m/N_s. (Pirotti, 2010)

3 RESULTS AND DISCUSSION

3.1 Tree Position Extraction of ALS

The tree-top detective methods are application the local maximum moving-window filter, in figure 5 show, the red bounds are estimation the error assessment, and the measurement of the area are 20m x 70m, which the bounds have ALS and TLS data. First, we are application the local maximum to process the ALS data. The CHM have a clear tree canopy as compared with DSM, and more tree-top have be detected.

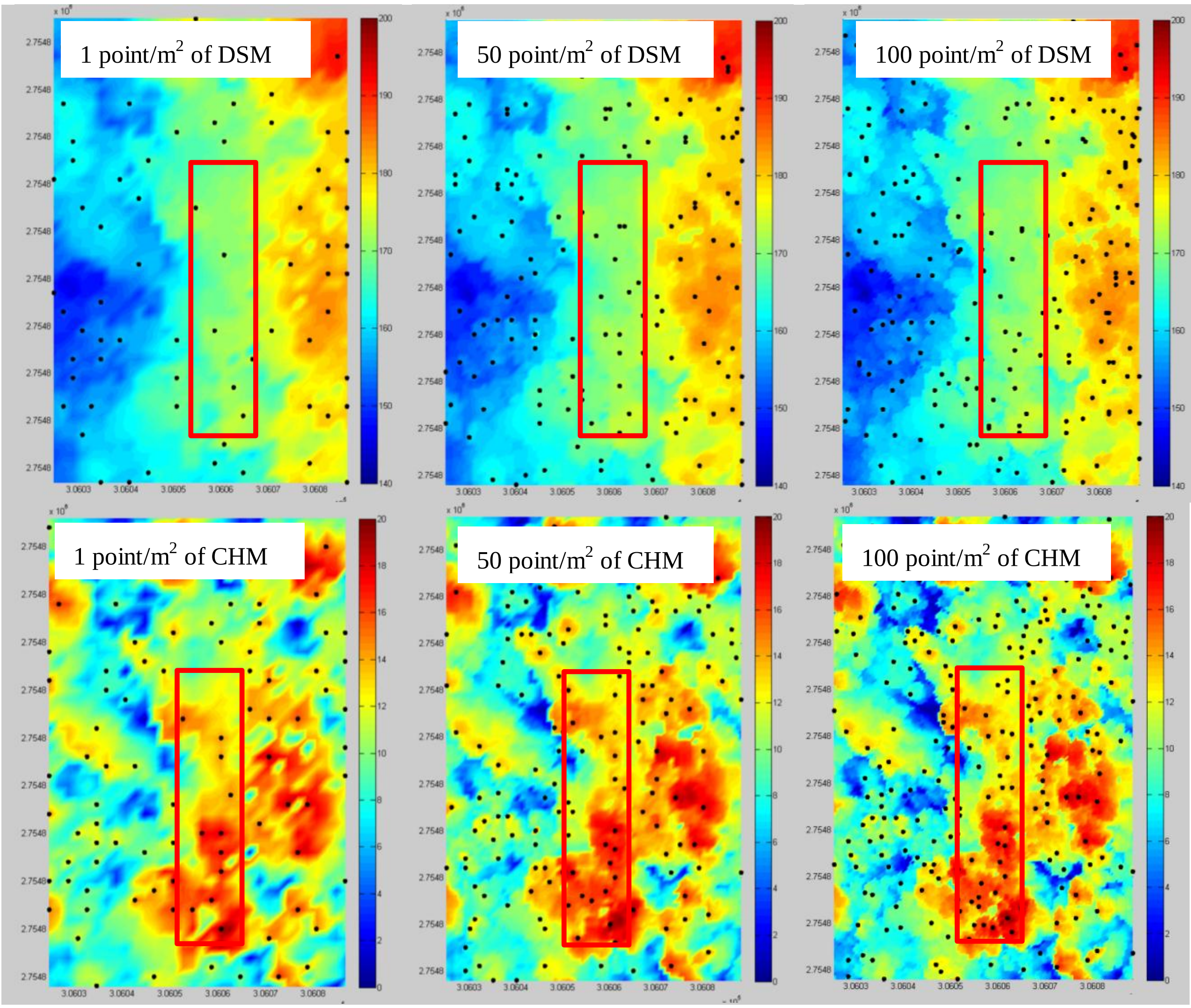

Figure 5. application the local maximum to extracting the tree position of CHM and DSM, red bounds are area of estimation the error assessment and black points are tree-top extraction.

3.2 Error Assessment

This study area had extracted 27 dominant trees from terrestrial laser scanner, which the total number of ground-truth surveyed tree positions (N_S) value was 27. In table 2 show, the point density will increase the coefficient of agreement (κ) and percentage of tree extraction (%) values, in other words, the lack of point density could not output high resolution models and high accurate tree positions. The coefficient of agreement (κ) and percentage of tree extraction (%) had a stable value which the point density will over than 10 points/m^2.

In this study, especially using the 100 points/m^2 density airborne lidar data to extracting the tree positions, the results show, the K value was 0.41, which the percentage of tree extraction value was 51.85% from DSM extracted, and K value was 0.64, which the percentage of tree extraction value was 70.37% from CHM extracted. Therefore, the point density up to 100 points/m^2 had a low accuracy error, because the DSM and CHM could showed the smaller crown breadth of tree. In figure 6 show, CHM and DSM methods all of could be distinguished the tree location, and CHM was better than DSM, increase point density will improve the position accuracy.

Table 2. Coefficient of agreement (κ) and percentage of tree extraction (%). N_S = total number of ground-truth surveyed tree positions, N_I = total number of lidar-inferred tree tops, N_C = commission error, N_O = omission error and N_m = number of matching (correct) points.

DSM	(N_s=27)					
Density	N_I	N_o	N_c	N_m	%	κ
100	22	13	8	14	51.85	0.41
50	19	15	7	12	44.44	0.27
40	20	15	8	12	44.44	0.27
30	21	15	9	12	44.44	0.27
20	18	16	7	11	40.74	0.20
10	22	16	11	11	40.74	0.20
5	6	24	3	3	11.11	-1.54
1	6	25	2	2	7.41	-2.67
CHM	(N_s=27)					
Density	N_I	N_o	N_c	N_m	%	κ
100	32	8	16	19	70.37	0.64
50	22	16	11	11	40.74	0.20
40	19	15	7	12	44.44	0.27
30	21	16	10	11	40.74	0.20
20	21	16	10	11	40.74	0.20
10	22	15	10	12	44.44	0.27
5	12	21	6	6	22.22	-0.38
1	11	22	6	5	18.52	-0.56

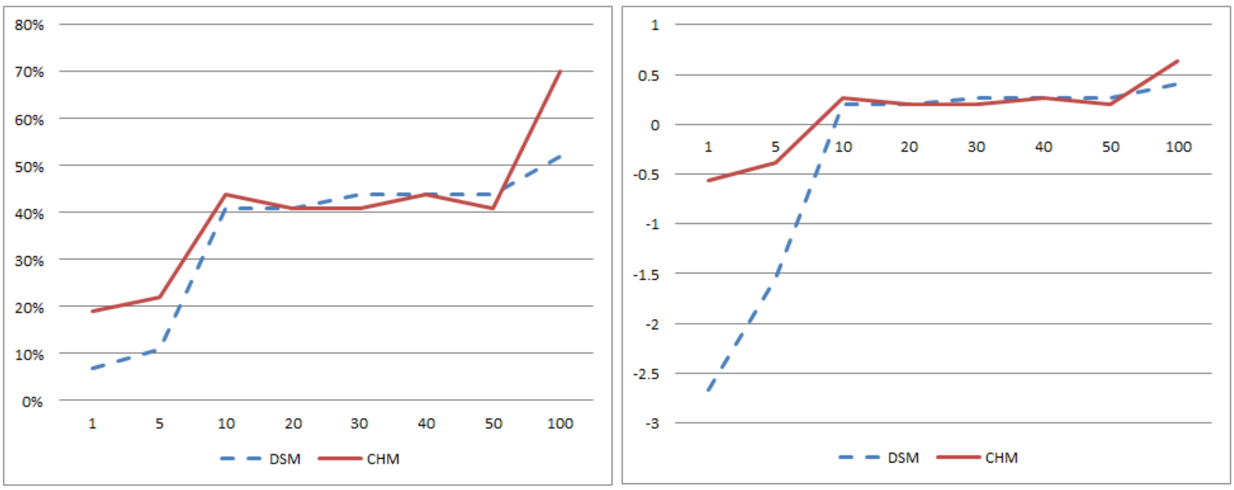

Figure 6. accuracy error of CHM and DSM methods

4. CONCLUSIONS

This local maximum method could be applied to stands with the preferred characteristic of having few or no dominant trees and where the canopy shape makes it difficult for other methods to give good results. Therefore, we were tested the different point cloud density to process the DSM and CHM data. The results show, the more quantity of point cloud had a better accurate error from the local maximum to detection the tree-top by DSM and CHM, because the higher quantity of point-cloud could mapped the smaller crown breadth of the tree.

The result of different in the DSM and CHM methods, the DSM method could not be enhance the distribution of tree crown, and the CHM method had effected to describe the tree crown. The majority of studies the point density is between 10 and 20 points/m^2, in this result the K and percentage of tree extraction had a stable value in the point density over than 10 points/m^2. This method could be applied to stands with the preferred characteristic of having few or no dominant trees and where the canopy shape makes it difficult for other methods to give good results. The ability to obtain stand density and spatial distribution of its elements over large areas using a semi-automatic process can be of great help as input to inventories and as parameters for derived ecological indices. Also less ground-truth surveys would be needed and could just be used to control the results, bringing an economical advantage.

5 REFERENCES

Puttonen, E., J. Suomalainen, T. Hakala, E. Räikkönen, H. Kaartinen, S. Kaasalainen, and P. Litkey, 2010. Tree species classification from fused active hyperspectral reflectance and LIDAR measurements. Forest Ecology and Management, 260, pp.1843-1852.

Forzieri, G., L. Guarneri, E. R. Vivoni, F. Castelli, and F. Preti, 2009. Multiple attribute decision making for individual tree detection using high-resolution Laser scanning. Forest Ecology and Management, 258, pp.2501-2510, 2009.

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

Popescu, S. C., R. H. Wynne, and J. A. Scrivani, 2004b. Fusion of small-footprint lidar and multispectral data to estimate plot-level volume and biomass in deciduous and pine forests in Virginia. USA Forest Science, 50(4), pp. 551-565.

Hyyppä J., and M. Inkinen, 1999. Detecting and estimating attributes for single trees using laser scanner. Photogramm. J. Finl.,16, pp. 27-42.

Suarez, J.C., C. Ontiveros, S. Smith, and S. Snape 2005. Use of airborne LiDAR and aerial photography in the estimation of individual tree heights in forestry. Computer & Geosciences,31, pp. 253-262.

Barilotti, A., F. Sepic, E. Abramo, and F. Crosilla 2007. Improving the morphological analysis for tree extraction: a dynamic approach to lidar data. Int. Arch. Photogram. Remote Sens. Spat. Inf. Sci.36-3(W52), pp. 26-31.

Pirotti, F. 2010. Assessing a template matching approach for tree height and position extraction from lidar-derived canopy height models of Pinus pinaster stands. Forests, 1, pp.194-208.

Wulder, M., O. Niemann, and D. Goodenough 2000. Local maximum filtering for the extraction of tree location and basal area from high spatial resolution imagery. Remote Sensing of Environment, 73, pp.103-114.