A New Method for Individual Tree Detection Using Airborne LiDAR Pulse Data

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ABSTRACT: Airborne light detection and ranging (LiDAR) data is a good means to detect individual tree location and crown. Existing tree extraction methods use gridded digital canopy height model (DCHM) which is generated by digital elevation model (DEM) and digital surface model (DSM). In this study, a new individual tree detection method for coniferous forest was developed using raw LiDAR data. A generalized ellipsoid tree shape model was used. By hill-climbing method was used for parabola fitting method. The best fit tree shape model which had the lowest root mean square error was estimated. This tree shape model estimated tree position and crown shape parameters. Additionally, a method for estimating ground elevation by the penetrated pulses was developed. This method was tested at coniferous forest in Japan. Results were shown by a 2D and 3D view. The detected results were compared with field data. In total, 74 percent of the trees were detected correctly. Height of detected trees was estimated with average error of -0.17 m. Positional differences were estimated with standard error of 0.5 m approximately.

1. INTRODUCTION

Airborne light detection and ranging (LiDAR) data is possible to retrieve three-dimensional structure of object shape. In forestry, LiDAR data is expected to make monitoring and surveying easy. LiDAR sensor, which is on-board air plane, records roundtrip time and intensity of return laser beam. Each laser pulse supplies accurate position (*x, y, z*) by global positioning system (GPS) and inertial measurement unit (IMU). Recently, small footprint LiDAR (footprint size less than 1m) is gaining attention, because detail shape of an object can be retrieved. Detection of single tree is required for harvesting and calculating timber volume. Therefore, there are many studies to detect individual trees by small footprint LiDAR data. Hyyppä *et al*. (2001) have demonstrated that tree heights are measured accurately. Persson *et al*. (2002) have shown that the tree crown can be accurately measured.

Several studies use the raster gridded data which are digital surface model (DSM) and digital elevation model (DEM) generated by LiDAR pulse data. A digital canopy height model (DCHM) by the DSM and DEM can be generated, and individual trees are detected by local maximum filter and watershed segmentation algorithm. However, few studies have focused on using raw LiDAR pulse data for individual tree detection. We can regard raw LiDAR pulse data as a part of tree crown shape. Therefore, using geometric equation of a tree shape model, sampled raw LiDAR pulse data can detect a single tree.

The objective of this study is to develop a method to detect individual trees using raw LiDAR pulse data in coniferous forest.

2. MATERIALS

2.1 Study Area

The study area is located Aomori prefecture in northern part of Japan. The dominant tree species is Japanese Cedar (Cryptomeria japonica D. Don) which is the most popular conifer species in Japan. Three plots were used in this study. The plot 1 and 3 were even aged plantations. The plot 2 was young aged plantation.

2.2 Laser Data

The LiDAR data were acquired with the ALS50 by Leica Geosystem on 11 and 12 August 2004. The flight altitude was approximately 1829 m (average) and its speed was 110kt (average). The overall pulse rate was 46 kHz. A ground cross-sectional diameter (footprint) for each laser beam was 0.47m. This sensor can detect 4th return pulses by each laser beam. Therefore, an average point density was approximately 10 points/m^2.

2.3 Field Data

Field data were collected at the same time as LiDAR data acquisition. The tree position, tree height and the number of trees were obtained at each plot. Differential GPS (GPS Pathfinder Pro/XR by Trimble Inc) was used for specifying a reference point. From the reference point, the laser range finder (LaserAce300 by MDL Inc) determined the tree position.

3. METHOD

In this study, we used the generalized ellipsoid tree model by Sheng *et al*. (2001) as the tree crown shape model. Coordinates of the tree top (*Xt, Yt, Zt*), base height (*bh*), crown height (*ch*), crown radius (*cr*) and an adjusting coefficient for crown curvature (*cc*) are parameters of the model. Once these parameters are known, the coordinates (*X, Y, Z*) of any point on the crown surface can be modeled by:

$$\frac{(Z + ch - Zt)^{cc}}{ch^{cc}} + \frac{((X - Xt)^2 + (Y + Yt)^2)^{cc/2}}{cr^{cc}} = 1 \quad (1)$$

$$Zt - ch \le Z \le Zt$$

Fig. 1 shows the tree crown model described by 5 parameters.

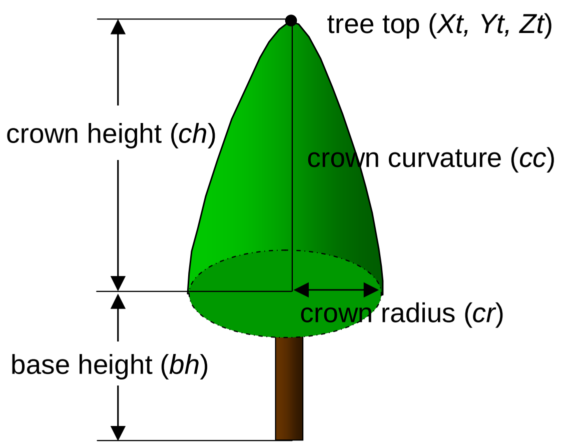

Fig.1 The geometric equation of a tree shape model by Sheng *et al.* (2001)

Using parabola fitting with this crown shape model, crown shape was detected. In this study, the hill-climbing method was used as parabola fitting method. The variables for hill-climbing method were 5 parameters. Firstly, the nearest tree top pulses were sampled (see 3.1). The nearest tree top pulse position was initial points of the hill climbing method. Around the tree top position, the pulses which represented tree crown shape were sampled. The range of *ch* and *cr* was specified by the sampled pulses (see 3.2). The parameters of *cc*, *Xt*, *Yt* and *Zt* were moved to neighborhoods. The best fit model parameters which had the lowest root mean square error (RMSE) were determined (see 3.3).

3.1 Extraction of a nearest tree top pulse

The nearest tree top pulse has highest elevation, compared to neighboring pulses within several meters from its pulse. The number of neighboring pulses whose elevation is higher than its elevation was counted at each pulse. If the number of that was 0, the pulse was extracted as a nearest tree top pulse. This method is similar to local maximum filter.

3.2 Sampling strategy

When the profiling position is away from the tree top, the elevation decreases (lesser than tree top). Therefore, if the profiling position moves straightly from the tree top position to outside, the elevation has been in decline. If the profiling position reaches other tree crown, the elevation increases. If the profiling reaches at a ground, the elevation decreases widely. These rules were applied to sampling pulses.

First, the pulses which were extracted around nearest tree top pulse position were divided into equal directional and length zones around *Xt* and *Yt*. The pulses which have maximal elevation were sampled at each zone. Secondly, profiling was started from the tree top position at each equal direction. If the elevation (1) increased or (2) decreased more than threshold value, the profiling was stopped. Front (stopped) zones were specified at each equal direction. Profiled pulses of each zone were sampled for model fitting within upper quartile 2D distance from the tree top to front zone pulses, because there were short profiling (overlapping nearby tree crown) and long profiling (profiling at a nearby tree crown). The parameters of *ch* and *cr* were determined by the sampled pulses.

3.3 Model fitting

If all parameters were specified, the radius at Z could be specified by equation (1). Therefore by the radius at Z and 2D distance between the tree top coordinates (*Xt*, *Yt*) and a pulse position, a error was calculated. By the all sampled pulse, the root mean square error (RMSE) was calculated. The RMSE was a score for the determination of this crown shape model by the hill-climbing method.

3.4 Ground elevation at tree coordinates

The pulses which reached the ground surface were used for predicting a ground elevation at detected tree position. If the difference value (*Zt* and the elevation of a pulse) was less than base height (subtracting *ch* from *Zt*), the pulses were extracted. The extracted pulses were divided into equal directional and length zones. The pulses which had minimal elevation were extracted at each zone. There were the zones which has no ground pulse. Therefore a pair of symmetrical equal directional zones and the nearest distance from tree coordinates (*Xt*, *Yt*) was extracted. 2D distance from tree positions and difference of ground elevation were used for calculating ground elevation by retable distribution.

4. RESULTS AND DISCUSSION

The developed method was done the test at each plot. Fig. 2 shows the results of tree detection at each plot. Maximal elevation at each plot of DCHM was 25, 13 and 23 m respectively. Detected tree positions corresponded to local maximal elevation of DCHM (Fig. 2b). Detected tree crown areas did not segment between crown gap areas where the DCHM elevation was low (black pixel). Fig. 3 shows an example of model fitting. Scattered points show sampled points which were plotted elevation (Y-axis) versus distance from the tree position (X-axis). Fitted parameters were *ch*: 11.25(m), *cr*: 2.44(m) and *cc*: 1.8. The tree top elevation and nearest tree top's elevation were 252.78 m and 252.88 m, respectively. The line curve corresponded to the sampled pulses. Fig. 4 shows 3D view at the part of plot 1. Each crown shape was rendered by fitted crown shape model. Tree shapes were rendered on the flat surface.

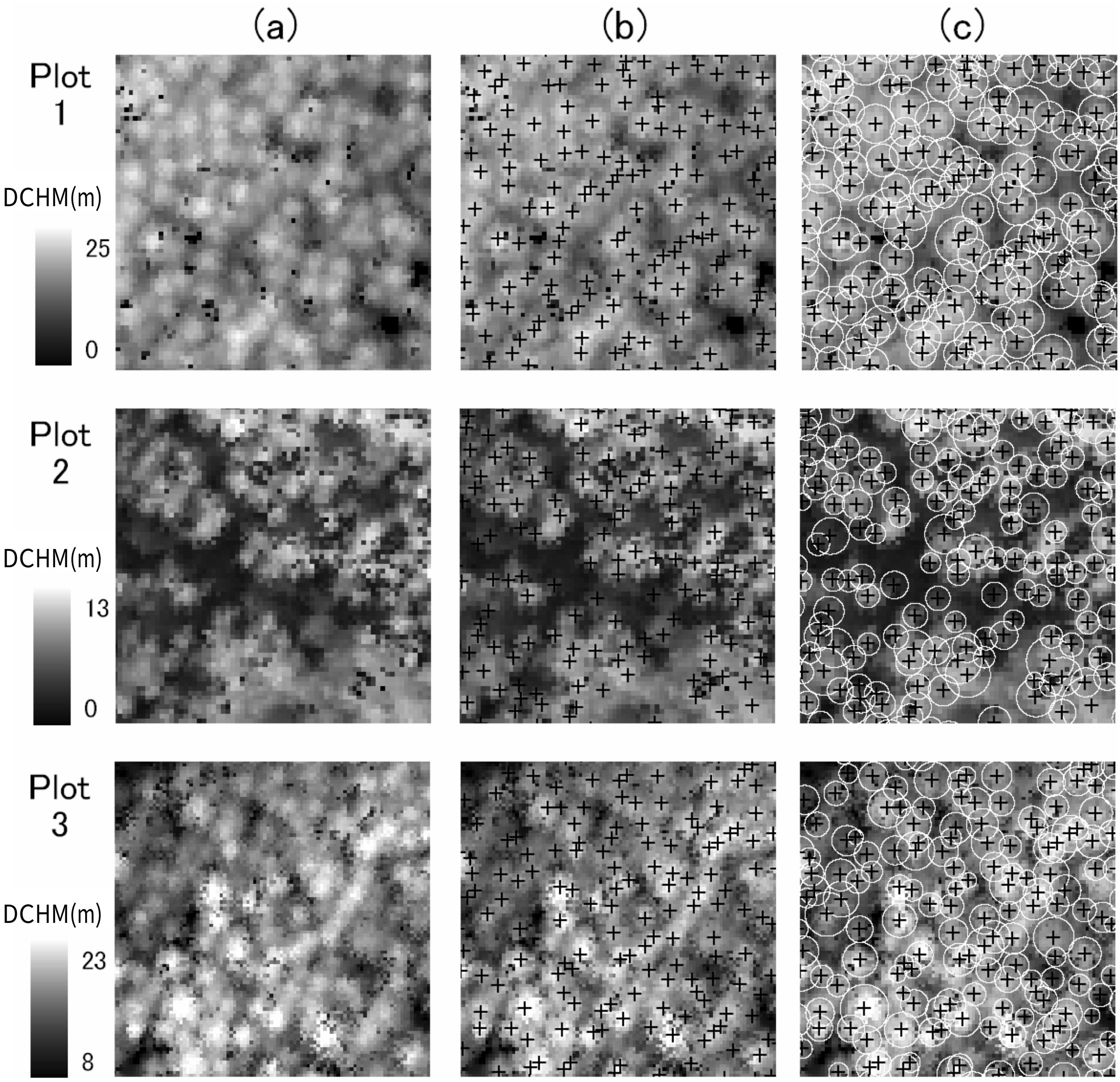

Fig.2 Results of tree detection. (a) The digital canopy model. (b) Detected trees positions (+ marks). (c) Detected tree positions (+ marks) and crowns (white circle line).

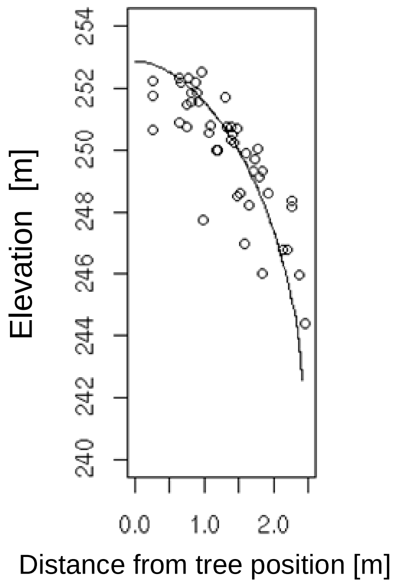

Fig. 3 Scatterplot of sampled pulse. The curve shows fitted model.

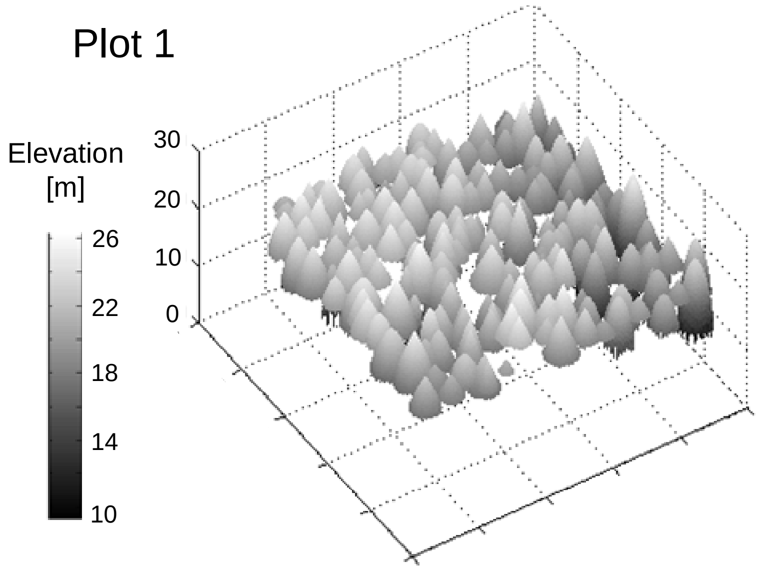

Fig. 4 A 3D view at the part of plot 1.

To evaluate the results, each detected tree was linked to the field data. The field tree that was within *cr* and closest to the position of detected tree was linked to the detected tree. However, crowns overlapped each other. A field tree may link to more than two detected trees. The field trees which linked to more than two detected trees were linked to the closest detected tree. The detected trees, whose link was broken, were linked other field tree which is not linked and within *cr*.

Number of trees at Plot 1-3 were 90 (81.8 %), 126 (73.7 %) and 81 (68.4 %), respectively. In total, 74.4 % of the trees were detected correctly. Most of the undetected trees were probably suppressed trees, because tree height varies by the circumstance in spite of same age at each site. Other studies point out the difficulty of detecting understory trees.

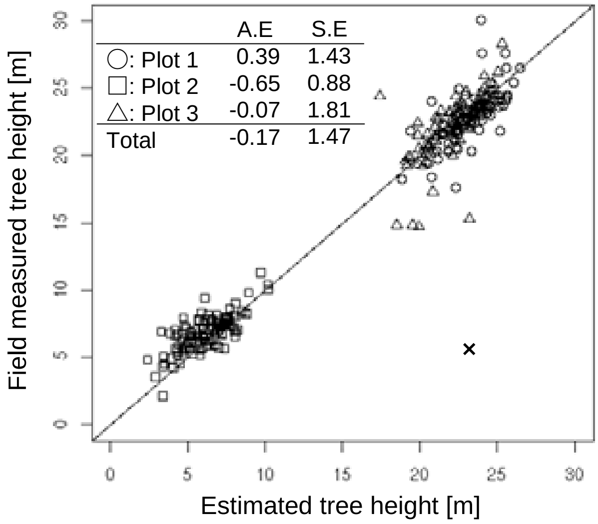

Fig. 5 Estimated tree height plotted against field measured. ×-mark shows the incorrectly linked tree. The A.E and S.E show “average error” and “standard error”, respectively.

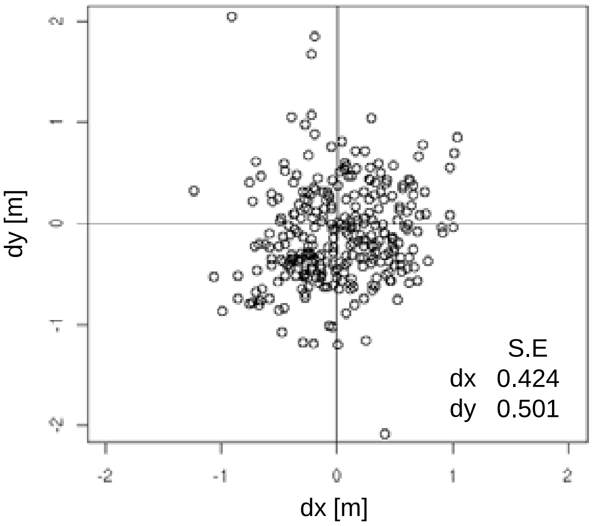

Fig. 6 Positional differences of estimated tree positions. The S.E means “standard error”

In Fig. 5, the estimated tree height is plotted against field tree height. Average errors of each plot were 0.39 m, -0.65 m and -0.07 m, respectively. In total, average error was -0.17 m. In conifer forest, the underestimation of tree height is generally explained by the failure of sampled tree top. The underestimation of tree height might be reduced by our developed method, because tree top elevation estimated by fitting model was higher than near tree top pulse. Moreover, Gaveau and Hill (2003) pointed out about such underestimation which is caused by leaf density or closure. The underestimation might be caused by low leaf density of young trees like in Plot 2, as evident from underestimations at plot 2. Obviously, accuracy of ground elevation influences tree height estimation accuracy. Locally, flat facet of topography was assumed in this method. Standard errors of each plot were 1.43 m, 0.88 m and 1.81 m, respectively. In total, standard error was 1.44 m. Hyyppä *et al*. (2001) stated that standard error of a field data was 1.8 m. Therefore, we conclude our standard errors as acceptable.

In the fig. 6, positional differences of estimated tree positions are shown. Standard errors of *x* and *y* were 0.424 m and 0.501 m, respectively. At each plot, median distance between each field position which was calculated by triangulation net was 3.2 m, 2.8 m and 4.1 m, respectively. Therefore, these standard errors are acceptable.

The developed method estimated 5 parameters. Especially, the parameters of *ch* and *cr* were directly estimated by sampled pulses. However, the pulses at the helm of crown may not be sampled in the dense forest. Therefore, in the dense forest *ch* and *cr* may be underestimated. Quantitative evaluation of tree crown shape is our future task.

5. CONCLUSION

In this study, new individual tree detection method was developed. This method used not DSM and DEM, but raw LiDAR data. The tree crown shape model was used for parabola fitting. The hill-climbing method was used for estimating tree position, height and parameters of tree crown shape. The developed tree detection method worked well for conifer forest.

Small-footprint LiDAR data can provide the small scale inventory for forest management, using developed method. Additionally, tree crown shape is important to estimation of crown interception of precipitation and evapotranspiration, forest fire and forest growth model. The developed method has the potential for the application of the forestry.

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