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Review

Current Status of Tree Height Estimation from Airborne LiDAR Data

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Abstract : Most nations around the world have expressed significant concern in the climate change due to a rapid increase in green-house gases and thus reach an international agreement to control total amount of these gases for the mitigation of global warming. As the most important absorber of carbon dioxide, one of major green-house gases, forest resources should be more tightly managed with a means to measure their total amount, forest biomass, efficiently and accurately. Forest biomass has close relations with forest areas and tree height. Airborne LiDAR data helps extract biophysical properties on forest resources such as tree height more efficiently by providing detailed spatial information about the wide-range ground surface. Many researchers have thus developed various methods to estimate tree height using LiDAR data, which retain different performance and characteristics depending on forest environment and data characteristics. In this study, we attempted to investigate such various techniques to estimate tree height, elaborate their advantages and limitations, and suggest future research directions. We first examined the characteristics of LiDAR data applied to forest studies and then analyzed methods on filtering, a precedent procedure for tree height estimation. Regarding the methods for tree height estimation, we classified them into two categories: individual tree-based and regression-based method and described the representative methods under each category with a summary of their analysis results. Finally, we reviewed techniques regarding data fusion between LiDAR and other remote sensing data for future work.

Key Words : LiDAR, tree height estimation, biomass, filtering, DTM, data fusion.

1. Introduction

At present, people around the world are interested in the problem of climate change due to an increase of green-house gases in concurrence with an enforcement of an agreement for global environment in order to reduce the amount of six kinds of green-house gas emission including carbon dioxide through Kyoto Protocol, which is an international agreement for controlling and preventing global warming. Especially, Kyoto Protocol considers forest resources as a source of absorbing carbon dioxide in which the carbon absorption by forest biomass is recognized as gas emission reductions. Therefore, technology on forest resource measurement customized to the different characteristics of forest in each country is

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essential. This results in current active studies on estimating forest biomass (Lefsky *et al.*, 2001; Patenaude *et al.*, 2004; Goodwin *et al.*, 2006; Hollaus *et al.*, 2007; Popescu, 2007; Zhao *et al.*, 2009). It is important to figure out the problems and critical points from previous studies as forest characteristics are very diverse according to location and climate and a clear definition of biomass and standard mathematical model for its estimation has not been established yet.

Forest tree structure is important for the analysis of forest ecosystem process, and measurements about it are essential for monitoring, modeling and managing forest (Sexton *et al*, 2009). Forest measurements generally includes meaningful tree characteristics which can be measured within forest areas, such as tree height, DBH (diameter at basal height), species of trees and the number of trees.

With traditional forest inventory methods, it is possible to obtain forest measurements technically simply only at the sample plots of the forest, but it is hard to perform this work in mountainous terrain and closed forest (Andersen *et al.*, 2006). Actually, it is almost impossible to perform such field survey on the entire area of widely-spread forest. On the other hand, airborne and satellite-borne sensors provide data from wide-range of forest areas economically and efficiently, which result in various studies on forest measurement using remote sensing data (Næsset, 1997). Active remote sensors, especially LiDAR (light detection and ranging) system, enable to estimate vertical structure of wide-range of forests with high accuracy more efficiently (Lefsky *et al.*, 2002a).

Among forest measured factors, tree height is one of the most essential and fundamental measurement for quantitative assessment of tree growth and biomass estimation (Andersen *et al.*, 2006). Lim *et al.* (2003) estimated maximum laser height from LiDAR data, mean laser height calculated from all LiDAR returns, and mean laser height calculated from data filtered using intensity information, and performed regression analysis with forest measurements obtained in the field. The analysis result showed that many forest characteristics are highly correlated such as BA (basal area) and aboveground biomass. As tree height has a close relationship with the forest resources information and can be measured quantitatively, studies for estimating tree height have been conducted actively. The recent active researches include tree height estimation using airborne LiDAR (Nilsson, 1996; Næsset, 1997; Hyyppä *et al.*, 2001; Popescu *et al.*, 2002; Lefsky *et al.*, 2005; Andersen *et al.*, 2006; Coops *et al.*, 2007; Tesfamichael *et al.*, 2010), tree height estimation by combining airborne LiDAR data with satellite optical or SAR images (Andersen *et al.*, 2003; Suárez *et al.*, 2005; Hyde *et al.*, 2006; Hyde *et al.*, 2007; Sexton *et al.*, 2009, Sun *et al.*, 2010), and tree height and DBH estimation using terrestrial LiDAR systems (Bienert *et al.*, 2006; Huang, 2011).

Methods of estimating forest information can be largely divided into 1) individual tree-based methods and 2) regression-based methods (Maltamo *et al.*, 2005). The individual tree-based methods are a technique to estimate the number of trees, tree height and horizontal distribution of trees quantitatively by detecting individual trees from the forest area, and various kinds of algorithms have been suggested for detecting individual trees (Perssen *et al.*, 2002; Koch *et al.*, 2006; Lin *et al.*, 2011). In Korea, the individual tree-based methods have mainly been used to estimate forest parameters including the number of trees and tree height. Chang *et al.* (2006) segmented individual tree crowns and estimated the tree heights using a watershed algorithm and a local maximum filter. Also, Woo *et al.* (2007) applied a moving window operation to CHM (Canopy Height Model) to extract the peak points of individual tree crowns and estimated the number of trees and the tree heights. The regression-based method is to estimate forest structure based on statistical methods such as an analysis of vertical distribution of trees and average tree height estimation about the data obtained within a specific area. The detailed descriptions will be explained further in Section 4.

LiDAR systems can be generally categorized into discrete or waveform LiDAR systems according to the output data type. Discrete LiDAR systems have relatively small footprints (0.25-1m) while waveform systems has larger footprints (10-100m) (Hudak *et al.*, 2002). Waveform LiDAR systems provide full-waveform data about each individual pulse by sending one laser pulse and receiving continuous pulses reflected within wide footprint. Since the full-waveform data includes pulses reflected from the ground and from the top of trees, maximum tree height and average tree height can be estimated by detecting the location of pulse peak reflected from the ground and the top of trees. Typical waveform LiDAR systems include GLAS (Geoscience Laser Altimetry System), LVIS (Laser Vegetation Imaging Sensor) and SLICER (Scanning LiDAR Images of Canopies by Echo Recovery) (Sun *et al.*, 2008). Although waveform systems are more complex in data processing than discrete LiDAR systems, they are promising and useful in forest studies (Hudak *et al.*, 2002; Maltamo *et al.*, 2005).

Discrete LiDAR systems have been widely used in various fields such as building modeling, target detection, obstacle avoidance and terrain mapping as well as in forest applications. Discrete LiDAR systems send one pulse and can receive multiple return pulses, but generally provide first return and last return including the location coordinates with intensity information. First return tends to record a signal reflected for the first time while last return records a signal passing through the tree and reflected finally, for example, on the ground surface under the tree. A study on tree height estimation using such a property was performed by Hyde *et al.* (2007).

Forest studies employ airborne LiDAR data to estimate and investigate forest resources information by applying a specific process and algorithm to various forest environments. Since there has been no standard for the input LiDAR data properties and the output verification process in forest applications, it is difficult to compare the results of various forest studies absolutely. Moreover, the methods applied to each study have their own advantages and limitations according to the data used and characteristics of trees. Thus, in order to perform forest study using LiDAR data in future, it is necessary to classify and summarize the methods of the existing studies systematically.

The purpose of this study is to investigate the advantages and limitations of the current forest studies using airborne discrete LiDAR data by analyzing widely used methods, especially the studies on tree height estimation. In this paper, the methodology used to perform this study is first explained and the properties of LiDAR data for forest studies are discussed. The study then analyzes major algorithms on filtering, a preprocessing procedure of LiDAR data and examining advantages and limitations of two methods in major study cases for tree height estimation. Finally, the work presents a plan for study on forest investigation from the fusion of LiDAR and other remote sensors.

2. Methodology

This paper involves rich literature review in major overseas journals related to remote sensing such as Remote Sensing of Environment, Forest Ecology and

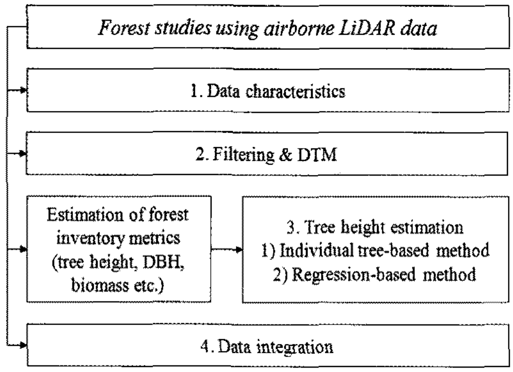


Fig. 1. Classification of forest studies using airborne LiDAR data.

Management, and Photogrammetry and Remote sensing in order to analyze forest studies using LiDAR data, and refers to theses presented in proceeding of Silvilaser, an international conference about LiDAR application for measuring forest ecosystem and international academic conferences. The collected research studies are classified into researches on filtering and DTM (digital terrain model) generation, techniques to estimate various kinds of forest measuring factors and techniques using LiDAR and other remote detecting sensors. The research studies to estimate forest metrics are largely composed of studies estimating tree height or biomass, which can be classified into individual tree-based method and regression-based method according to the method of data processing. This paper focuses on the method of estimating tree height. The work involves analysis of the characteristics of LiDAR data and its preprocessing procedure. Also, as studies on tree height estimation using LiDAR data have been conducted actively until now, the study examines the techniques on combining LiDAR and other remote sensing data. Fig. 1 shows classification of forest studies using airborne LiDAR data.

3. Data Characteristics

LiDAR data obtained from discrete LiDAR system shows various types of characteristics according to the system and forest environmental conditions. Accordingly, it is necessary to figure out the characteristics of the acquired LiDAR data in order to select an appropriate data processing method.

Generally, as the point density of LiDAR data is higher and the size of footprint is smaller, it would be more helpful to estimate individual tree location and tree height minutely. Persson *et al.* (2002) used LiDAR data having various sizes of footprint (0.26 m, 0.52 m, 1.04 m, 2.08 m, 3.68 m) in order to estimate individual tree and tree height. The results of detecting individual tree showed 66% of detection rate in data having 3.68 m of footprint, while 71% of sensing rate in data having 0.26 m of footprint, and also as for tree height, RMSE with field measurements reduced as footprint was smaller.

Point density of LiDAR data used in forest studies varies from 1 or less to 10 or more per m^2. Brandtberg *et al.* (2003) used data with about 0.1m of footprint and about 12 returns/ m^2 of point density in order to estimate tree metrics using LiDAR data acquired in winter. Maltamo *et al.* (2005) used data with 10 returns/m^2 of point density for analyzing tree height distribution in plot area and understory vegetation using histogram. Suárez *et al.* (2005) estimated tree height with high accuracy (R^2 =89) using data with 3-4 returns/m^2 of point density. It seems that estimation of forest information according to point density is related to tree distribution in the forest and the characteristics of trees such as age-class. In case that age-class and species of trees in the target area are similar, metrics values such as DBH are also similar. Fig. 2 shows metrics of an individual tree. Therefore, the characteristics of trees spreading over wide areas can be figured out more accurately

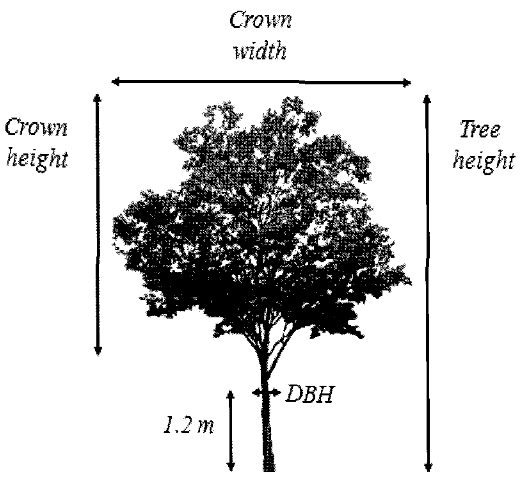


Fig. 2. Forest inventory metrics.

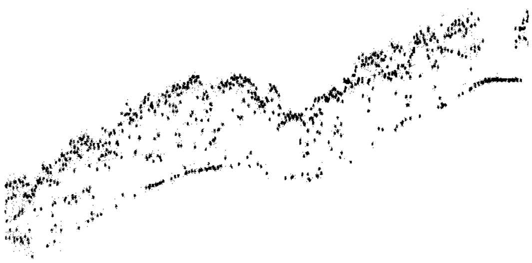
with fewer samples.

In case that there are many kinds of trees with various heights and that the shape of crown is narrow and long, it is hard to estimate the height and distribution of trees accurately with low point density. That is, though high point density has an advantage that it can model the tree structure more accurately, it is possible to estimate tree characteristics even with low point density according to the characteristics of forests. Therefore it is necessary to conduct a study on selecting appropriate point density considering expected accuracy. In case of deciduous forests that they have dramatically changed crown conditions according to seasons and crown closure is high in summer, this results in having very few LiDAR data reaching to the ground. Hendrix (1999) showed that 93% of LiDAR data obtained in forest of mixed deciduous trees in Aiken area of South Carolina did not reach the ground (Jensen, 2000). Similarly, in case of high crown closure of trees, degree of accuracy of forest estimation can be relatively low. Thus, Wagner *et al.* (2004) generated DTM from LiDAR data acquired under leaves-off and leaves-on conditions in forest areas using hierarchy robust filtering technique and compared them. As a result of the comparison, LiDAR data obtained in winter had high penetration ratio to the ground and is possible to generate more accurate DTM. LiDAR data acquired in summer had low penetration ratio while DSM (digital surface model) presented the top of the trees more exactly. This indicated that it would be possible to obtain more accurate tree height model by subtracting a winter DTM from the corresponding summer DSM.

4. Filtering

In order to estimate tree height from LiDAR data acquired in forest areas, filtering should be applied to remove the effects due to the height and slope variation of the ground in forest areas before estimating tree height. Filtering means a process of classifying ground points from LiDAR data. Fig. 3 shows a result of filtering operation applied with a slope-based method.

As the DTM generated from classified ground points (Fig. 3b) is used to estimate tree height, it is an important preprocessing procedure for tree height estimation. Many studies on filtering have been already performed. Axelsson (2000) studied a method of classifying ground points from LiDAR data using an adaptive TIN model at the same time generating DEM. This classifies LiDAR data with wide-distant grid and extracts seed points which are assumed to be ground points within each grid. It adds points which are assumed to be ground points to TIN by calculating threshold parameter of distance and angles with TIN facets after creating TIN from the seed points. It generates final ground DEM by repeating such a process until there is no added point. This algorithm applied to TerraScan, one of commonly-used software for processing LiDAR data and Maltamo *et al.* (2005), Coops *et al.* (2007) and



(a)

(b)

Fig. 3. (a) LiDAR data in forest areas. (b) Ground points classified after filtering.

Lin *et al.* (2011) used TerraScan for classifying ground points in forest studies using LiDAR data. Besides, various approaching methods were suggested including slope-based filtering (Vosselman, 2000; Sithole, 2001) and morphological filtering (Keqi *et al.*, 2003; Arefi and Hahn, 2005). Sithole (2001) used a slope map of filtered areas in order to supplement problems caused when threshold was fixed to a specific value in existing slope-based filtering. As a result of comparing it with TerraScan filtering applied with adaptive-TIN filtering, it could remove non-ground points without discarding many ground points compared with TerraScan filter. Especially, filtering for forest areas (Kraus and Pfeifer, 1998; Raber *et al.*, 2002; Kobler *et al.*, 2007; Tang *et al.*, 2008) suggested appropriated methods considering geographic features of the forest.

After distinguishing between ground points and non-ground points through filtering, it is possible to generate DTM from the ground points. Generally, as forest areas include slope, flat terrain heights of non-ground points is calculated by subtracting DTM values from all height values of LiDAR data obtained in forest areas. The heights of non-ground points estimated in this way represent vertical structure distribution of trees removing slope heights. Forest studies estimate forest information using those non-ground points directly, or use them to figure out distribution of tree height by generating DSM which is called CHM.

The major purpose of filtering in forest areas is to classify the ground points from LiDAR data reflected from trees and the ground. Since there are quite many complex features and various species of trees mixed in actual forests, it is not a simple task to classify data reflected on the ground using LiDAR data only. Especially, in case of high density of the tree crown and low point density of LiDAR data, the number of ground points classified through filtering is low, making the accuracy of DTM lower. Accordingly, when conducting forest studies using LiDAR data, it is necessary to determine whether it is appropriate data for detecting the ground surface in forest areas or not. This can be done by computing the ratio of ground points and all LiDAR points or measuring the number of ground points in a sample area. Additionally, other remote sensing data can be used to filter LiDAR data points.

5. Tree Height Estimation

Non-ground points represent the vertical structural distribution of forest. Methods of estimating forest information using such data can be divided into individual tree-based methods and regression-based methods. The individual tree-based methods extract individual trees by applying image processing techniques to CHM which convert three dimensional LiDAR data into gray-scale images according to altitude, while the regression-based methods derive forest information by applying statistical techniques to the point data.

1) Individual tree-based methods

The individual tree-based method estimates tree information such as the number of trees, tree height and horizontal distribution after sensing individual tree distributed in forest areas. In order to identify individual trees, a method using watershed segmentation (Soille, 1999; Schardt, *et al.*, 2002; Chang *et al.*, 2006) and local maximum filtering (Persson *et al.*, 2002; Popescu *et al.*, 2002) are mainly used. The watershed segmentation algorithm is one of image processing techniques, which classifies tree crown areas of individual trees by extracting border lines between the tree crowns in CHM, gray-scale images. It determines the tree location and height using the highest cell values within the classified individual tree crown area. Popescu *et al.* (2002) extracted individual trees by assuming the highest altitude value among the data acquired from the same tree crown as an apex of the tree and by applying local maximum filtering to CHM. At this time, the size of a window used for filtering should be similar to that of individual tree crown which is expected to be observed. Basically, the higher the tree height is, the bigger the size of tree crown is. Accordingly, it performed on-site investigation of total 189 trees and established a relation equation between the tree height and the crown size of a tree. Using this relation, various sizes of individual trees were extracted by changing the size of a window according to the height of CHM (Fig. 4).

However, such a method of individual tree extraction has a disadvantage that it needs advance information about the shape and size of the tree crown. As the size of tree crown is quite various, with a fixed size of window, the accuracy of the tree extraction can be lowered. Lin *et al.* (2011) extracted

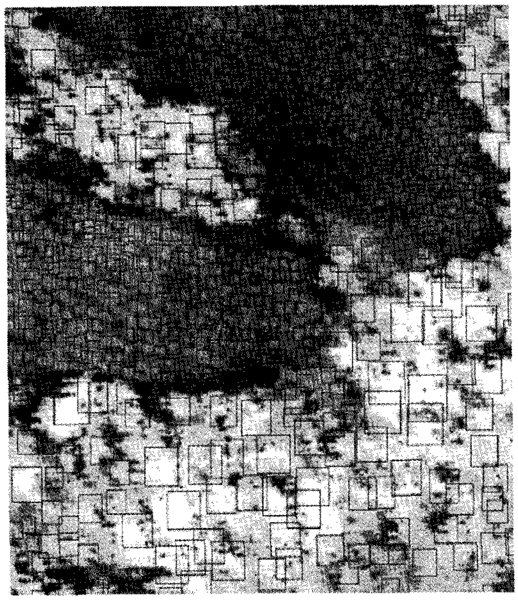


Fig. 4. Variable windows that identified tree tops (Popescu *et al.*, 2002).

the tree crowns of individual trees automatically by using multi-level morphological active contour algorithm (MMAC) which supplemented the disadvantages of the existing algorithms for individual tree extraction. MMAC extracts the border line of tree crown of individual tree by applying bottom up erosion, top down dilation and active contour model to CHM. This identifies the apex of tree crown area and delineates the border of tree crown by identifying the object by each height value of images without using a specific window. The individual tree-based method is hard to identify the lower trees when forests have various species of trees and multi-layered structure, and its accuracy can be lowered in case that the shape of tree crown is not appropriate for individual tree extraction, but it has an advantage to provide more quantitative forest information.

2) Regression-based methods

The regression-based method applies a general statistical technique to LiDAR data measurements distributed in wide plot areas. It extracts meaningful forest information by analyzing distribution and density of the measurements without necessarily deriving a CHM by subtracting a DTM from LiDAR points. Næsset (2002) estimated characteristics of many trees in each 200 m^2 of a sample plot area. He determined quantiles of 0, 10, ···, and 90 percentile about vertical height distribution of LiDAR data in the sample area and estimated maximum, minimum, coefficient of variation and density of trees. He also evaluated the accuracy of average height, dominant height and mean diameter with the comparison of field measurements. Maltamo *et al.* (2005) examined forest structure composed of many kinds of trees using HistMod algorithm based on histogram analysis. The size of sample plots is around 30m × 30m and average height of understory trees is estimated by judging whether histogram of LiDAR data included to the plot is multi-layered structure or not. The distribution of LiDAR data is generally represented in Fig. 5 which is a histogram of 182 points within the 10m × 10m size of plot. When the density of understory vegetation is high, the data frequency data with low height is shown high.

HistMod algorithm first creates a histogram which represents the frequency of non-ground points according to their height from the ground. It calculates Lloyd's threshold (the first vertical bar from the right in Fig. 6) which classifies overstory and understory trees and determines multi-layered structures from the difference between maximum frequency (MaxFreq) and minimum frequency (MinFreq) of the understory trees located in the left side (Fig. 6). As the regression-based methods estimates forest biophysical properties based on a plot area, the accuracy can be lowered relatively in comparison with the individual tree-based methods. However, it is possible to analyze data objectively using verified statistical techniques when estimating

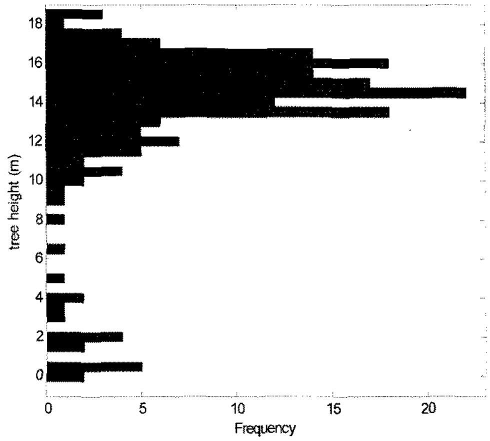


Fig. 5. Histogram of LiDAR data in a plot.

average values in the wide area or identifying the vertical structure of multi-layered forest.

6. Data Fusion

In order to estimate forest information in more detail, studies based on fusion of LiDAR system with other sensory data have been performed. Hudak *et al.* (2002) estimated and mapped tree height by combining LiDAR data and Landsat ETM+ data. Suárez *et al.* (2005) detected individual trees and estimated tree heights in forest areas by using LiDAR data and airborne images. Hyde *et al.* (2006) aimed to improve results from individual sensors by integrating LiDAR, InSAR, Landsat ETM+ and Quickbird data for tree height estimation. Tree height estimated by using a formula model including various variables extracted from four kinds of data showed more promising result (R^2 = 0.835) than that by the LiDAR sensor alone (R^2 = 0.757). Also, Hyde *et al.* (2007) predicted aboveground biomass of coniferous forests using LiDAR, SAR (FOEN) and InSAR (GeoSAR) data and performed a comparison with filed values, and established formula models in order to examine a synergy effect through data fusion.

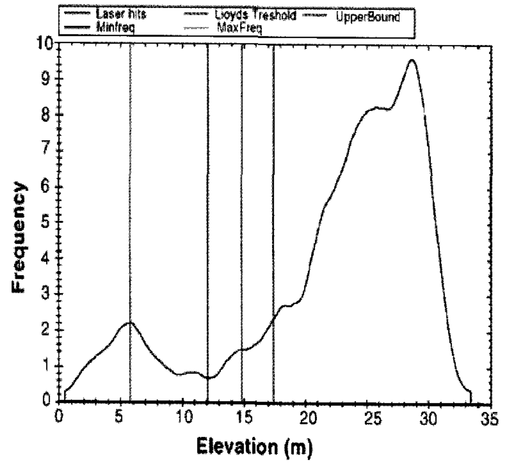


Fig. 6. Illustration of the HistMod algorithm (Maltamo *et al.*, 2005).

Major variables applied to the model include many kinds of heights (max, mean and percentiles) and response metrics which can be extracted from LiDAR and SAR data. As a result of regression analysis, when estimating by an individual sensor, LiDAR sensor showed the highest coefficient of determination (R^2 =0.837), and though it was improved to 0.868 as a result of analysis through three kinds of data fusion, it did not show a significant improvement. Sexton *et al.* (2009) tried to estimate tree heights from LiDAR, GeoSAR and SRTM data and compared them. As a result of regression analysis with field data, LiDAR, GeoSAR and SRTM showed coefficient of determinations (R^2= 0.83, 0.70, 0.54) respectively. Many forest studies based on data fusion use LiDAR data with high vertical accuracy and images with high horizontal accuracy and semantic information. Also, the studies using LiDAR and radar sensors are gradually increasing. As a result of analysis by employing various kinds of previous studies together, the individual sensor showing the highest accuracy in estimating tree height is a LiDAR, and in order to supplement disadvantages of LiDAR, data fusion is pursued for the improvement of the results. Generally, although LiDAR data can be the most useful for the generation of a DSM with higher resolution and accuracy than other kinds of data such as InSAR, they have some limitations in DTM generation. This is because as density of trees and tree crown closure ratio is higher, the probability of laser pulse of LiDAR sensors to pass through crown and reach the ground is sharply decreased. In this case, it is difficult to classify ground points by filtering from LiDAR data obtained in forest areas. Thus, it is advantageous to use DTM generated from InSAR (L-band) data, having averagely high accuracy despite relatively low resolution, as a reference.

7. Discussion

Airborne LiDAR systems generate data having various characteristics according to system types and operational variables. Forest ecosystem also shows different shapes, width and distribution of tree crown according to the location, climate and environmental conditions. Accordingly, a promising existing method for forest estimation applied to a forest area may not produce reasonable results from its application to other specific type of forest. Persson *et al.* (2002) detected individual trees in 12 plots classified according to species of trees and topography, and as a result, it showed almost 100% of detecting rate in plot 1, while it showed under 50% in plot 6 with the highest tree density. In addition, there were the cases where the first return could not be reflected from the top of tree accurately and the last return could not be reflected from the ground by penetrating trees. As LiDAR data provides spatial information about points, it is hard to identify the shape of tree crown and terrain accurately in case that the point interval is wide since the ratio of laser pulse which penetrates trees being reflected on the ground becomes lower when there is understory vegetation in the forest.

Thus, tree height estimated from discrete LiDAR data tends to be estimated too smaller than the real value. Accordingly, in order to extract exact forest information, appropriate data and algorithms should be used with the consideration of advance information about the forest. For example, if it is hard to sense the top of trees due to flat shape of tree crown, the regression-based method would be more appropriate than the individual tree-based method. Also, in order to generate DTM from LiDAR data in deciduous forest, it is effective to use leaf-off data attained in winter. Many studies using LiDAR data which has various characteristics according to forest topography, species of trees and shape of tree crown, and remote sensing data should be conducted constantly and construct the optimal methodology.

8. Conclusion

This paper classified and analyzed studies estimating biophysical properties of forest, especially tree height from airborne LiDAR data, and derived their advantages and limitations. Such studies have been performed up to recently with various subjects. As tree height shows high correlations with many forest biophysical properties, it is possible to estimate such metrics using tree height estimated from LiDAR data. Methods of tree height estimation can be divided into individual tree-based methods and a regression-based methods. When estimating quantitative and accurate forest information from LiDAR data with high resolution in a small area, the individual tree-based method is efficient, and in order to estimate general forest information in a wide area for estimating the amount of forest biomass, the regression-based method is appropriate. Though LiDAR data provides higher accurate forest information than other remote sensors, in order to acquire more improved results by supplementing the disadvantages of LiDAR data, studies on data fusion with other sensor data are also being progressed currently. Based on the analysis results from this study, we will pursue a further study on estimating and verifying forest biophysical properties including tree height by combining LiDAR data and SAR data.

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