Three Methods of Estimating Tree Attributes Using Remote Sensing Data

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Abstract: - The main objective of this study was to compare methods to estimate the number of trees and individual tree height using remote sensing data. A Korean pine tree study area for these techniques was selected. the methods of watershed segmentation, region-growing segmentation, and morphological filtering were compared to estimate their accuracy. The algorithm was initiated by developing a normalized digital surface model (NDSM) and classification with LiDAR data and aerial photography. The NDSM of the tree region was prefiltered and information about individual trees was extracted by segmentation and morphological methods. By using local maximum filtering, the tree height was obtained. Field observations were compared with the predicted values for accuracy assessment.
Key-Words: - Aerial photography, LiDAR, Tree modeling.

1 Introduction

For efficient and economical forest management, the accurate attributes of forests such as tree number, height, and diameter at breast height (DBH), have to be obtained easily. However, the traditional field-based process of obtaining a forest inventory is expensive, time-consuming, and inefficient [1]. In addition, field surveys for forest management have limitations in acquisition of information, because the area of concern is both huge and topographically difficult to access. Recently tree-modeling researches by remote sensing techniques have progressively considered.

Tree modeling by remote sensing has been studied by various researchers. For example, the intensity of a specific band of multispectral images is considered using a local maximum filter to find individual trees and to estimate basal area [2]. LiDAR (Light Detection and Ranging) sensors have the advantage over other methods of introducing the possibility of a fully three-dimensional analysis. Using an airborne laser system with a high sampling density, individual tree crowns can be detected [3], [4]. This makes it possible to detect their unique height and crown diameter. Using LiDAR data, the urban tree and tree free regions may be distinguished by elevation and intensity data [5]. There are limitations in previous research, because of its use of single data sources. Recent studies use both optical images and LiDAR data for tree modeling. Popescu et al. [6] show tree species classified by multispectral images and tree height estimated by a local maximum filter. Individual trees can be detected by a segment-based classification method and tree height estimated using a local maximum filter [7].

The most important objective in tree modeling is to detect individual attributes. Usually segmentation methods and morphological filtering are used typically. One of the major issues is what the best method for tree modeling is. This paper therefore reports on experiments carried out using color aerial photography and LiDAR data to decide on the best technique. An objective was to compare the detection techniques for individual tree attributes. Their accuracy in terms of tree numbers and heights mean was tested.

2 Study Site and Material

2.1 Remote Sensing Data

The data used for this study were acquired from airborne systems. Small areas of coniferous forest in Korea were selected for tree modeling. Aerial photographs (Fig. 1) and LiDAR data (Fig. 2) were acquired simultaneously on 26 April, 2005. The photograph resolution is 0.25×0.25 m and the point density of LiDAR Data is about 4 points/m^2.

2.2 Field Data

For accuracy analysis, we surveyed four sample plots of field data at two sites. Each forest plot was a fixed square. We only considered the needle-leaf trees because of season (early spring).

(a) Site 1 (b) Site 2

Fig. 1 Color Aerial Photograph

(a) Site 1 (b) Site 2

Fig. 2 LiDAR Data

3 Methodology

We proposed tree modeling by segmentation methods and compared each. Fig. 3 is a flowchart of the study.

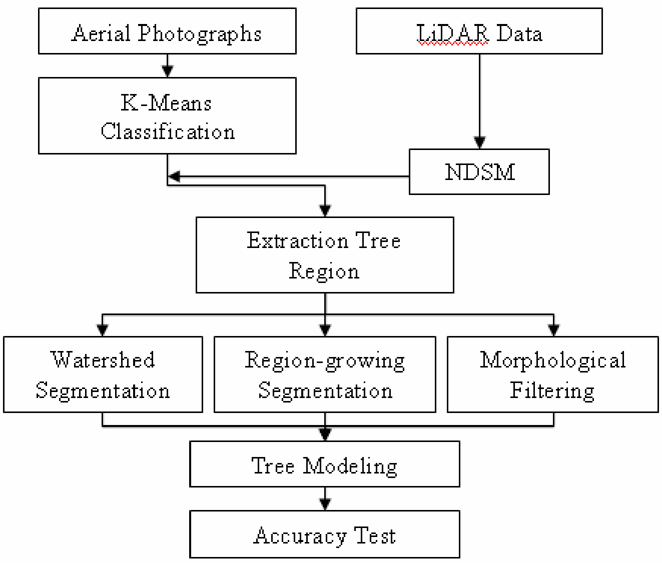

Fig. 3 Flow chart

3.1 Creation of an NDSM

A terrain map is a necessity for tree modeling. We made a digital surface model (DSM) using the first-return of LiDAR data. This is reflected from the surface of objects such as the soil, buildings, cars, leaves, and so on. The process aims to create a high resolution DSM interpolated from LiDAR data into a regular grid of 0.25×0.25m cells equated to the aerial photographs using an inverse distance weight (IDW) interpolation algorithm [11].

We created the digital terrain model (DTM) using morphological filtering from the DSM. Although the original morphological algorithm was developed for two-dimensional binary images, morphological filtering can be extended to three-dimensional grayscale images, where the grayscale values represent the intensity or another pixel attribute, such as elevation data. We applied morphological opening filtering to the DSM to eliminate aboveground objects. The size of structuring element was empirically determined by iterative process since the structuring element had a circular boundary and we did not need to eliminate all the aboveground objects, such as building circular.

The creation of an NDSM was achieved by subtracting a gridded image created from the first-return DTM. Superficial buildings, trees, and cars, were barely recognizable in the NDSM.

3.2 Extraction of Tree Region

The aerial photograph is classified by a K-means algorithm. We determined 15 empirically selected individual classes in the considered tree region. The results of the K-means classification include noise, since it is much simpler than other classification algorithms because the aerial photograph has only three bands (RGB). Therefore, we have to eliminate the noise of K-means classification with the NDSM.

We used various factors such as area, variation of elevation, and shape to eliminate noise [8]. Using an area threshold, the small objects, shrubs, and the structures of similar elevation to trees were eliminated. Cars and planar objects have a different elevation variation of pixels that distinguish them. Tree pixel elevation value is notably variable and greater than other objects. The shadow and shape of building components can be eliminated by their eccentricity, since a tree is typically near circular. We finally derived a layer that has information about a tree region.

3.3 Detecting Individual Trees

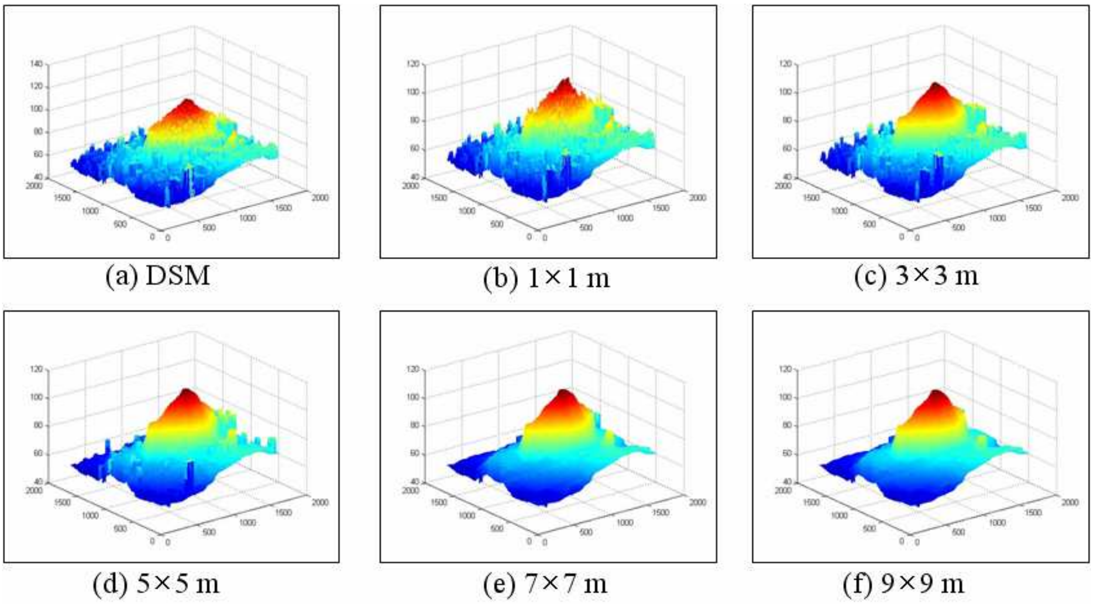

Fig. 4 Morphological filtering process by opening operation using variable mask sizes. Example obtained from site 3.

The efficiency of the core techniques in tree modeling is judged by their ability to detect individual trees. Segmentation subdivides an image into its constituent regions or objects on the discontinuity and similarity properties of pixels [12]. Morphological filtering can extract image components that are useful in the representation and description of regional shape. As a result, we were able to detect individual trees with LiDAR data, using various techniques.

3.3.1 Region –growing & Watershed Segmentation

Region-growing segmentation is a procedure that groups pixels or subregions into larger regions based on predefined criteria. This starts with a set of seed points, and from these, regions grow by appending to each seed those neighboring pixels that have properties similar to the seed points [12].

The local maximum filter detects a point that has values greater than any of its eight neighborhood values. The pixels that have the local maximum value are the seed points [1]. The eight pixels around a seed point are compared with the seed point pixel. If the values are similar to the seed, the pixels can be placed in the same region. The areas of the same label correspond in this model to individual tree crowns.

In geographical terminology, a watershed is the ridge that divides areas drained by different river systems. The geographical area draining into a river or reservoir is called a catchment basin. If rain falls on a surface, it is clear that water would collect in such basins. Rain falling on the watershed ridgeline has equal probability of collecting in either of the two catchments. Watershed segmentation locates the catchment basins and ridgelines [13] and applies these ideas to the grayscale image.

The grayscale image is considered as a topological surface, where the pixel values are interpreted as heights. We can detect individual trees and estimate tree height with local maximum filtering after watershed segmentation using the gradient magnitude.

3.3.2 Morphological Filtering

If a structuring element with a specified radius is used in morphological opening filtering of the NDSM, those areas of the NDSM in which the disk structuring element does not fit when pressed underneath the surface, such as the tops of individual conical or ellipsoidal tree crowns, will be removed through the opening operation. Top-hat filtering means subtracting the opened surface from the original surface. The tops of tree crowns remain in the NDSM, but the areas of other parts are removed. A thresholding operator is able to convert a top-hat filtered image into a binary one. Binary morphological opening filtering with a circular structuring element is sequentially applied to eliminate noise. These filtered operations can be carried out with a suitable structuring element to extract individual trees. Tree height is then estimated by local maximum filtering.

4 Result and Analysis

The accuracy in assessment of the number of trees and tree height had to be tested because field conditions in each test-plot were different and the pine trees were densely crowded. The estimated forest information was compared with field data using statistical techniques.

4.1 Ther Number of Trees

Because of the variation in plot areas, estimated tree numbers were compared with field observation by calculating tree numbers per unit area.

In the field, the forest trees are densly grouped. Not a few trees, which cannot be detected form the aerial system, are hidden around higher trees. Additionally, we only considered the needle-leaf trees in the study area.

After rejecting the plots with noise, R^2 greatly increased in the linear regression model. We can verify that the result for the watershed algorithm was the most accurate, but has instability. Morphological filtering has a stable algorithm, whereas the region-growing algorithm is neither accurate nor stable. The important point is that the field data closely correlated with the estimated values for the unchanged forest region.

Each method has a characteristic error. The watershed algorithm overestimates the number of treetops whereas the region-growing and morphological algorithms are each sensitive to parameters. Additional error is caused when LiDAR data are converted into a grid by interpolation.

Table 1. R^2 f the number of trees

Method	R^2 (After rejecting 3,4,5 plots)
Watershed segmentation	0.8003
Region-growing segmentation	0.0675
Morphological Filtering	0.6725

4.2 Tree Height

The tree-height accuracy assessment was a comparison of the estimated mean with field observations.

For accuracy assessment, we discriminated between mean estimated tree height and mean observed value for a T-test in each plot. Table 2 shows the result. The result of the T-test for five plots concluded that the estimated tree height related to observed field data at a 5% significance level.

We only considered the trees that could be definitely identified for individual tree-height accuracy testing. The same trees were chosen to compare the two data sets accurately and easily. A few trees were not seen in the image because of error in our model. Height error possibly occurred through interpolation of grid data from the LiDAR data following the signal not being reflected precisely from the treetops. A further possible reason could be the limited number of observations and the small size of plots. Accordingly, we must select a method appropriate to the image character to achieve tree modeling.

Table 3. T-test result of group tree height

ID	$P(T \leq \lvert t \rvert)$		
	Watershed segmentation	Region-growing segmentation	Morphological filtering
1	0.8666	0.2286	0.5748
2	0.5245	0.3693	0.4985
3	0.5302	0.3025	0.4760
4	0.2119	0.5079	0.2905

5 Conclusion

In this paper, we compared the three-methods of region-growing segmentation, watershed segmentation, and morphological filtering. We tested their accuracy in terms of numbers and heights. The NDSM was created by a morphological opening operation on LiDAR data and aerial photography that allowed tree region extraction. By using the segmentation and morphological methods with two-type data, the number and height mean of trees were calculated. Accuracy assessment showed watershed segmentation to be the best tree-modeling estimator whereas the region-growing algorithm gave the least less satisfactory result.

A limitation of this research we have to note is that segmentation and filtering methods used are very image dependent. To be more specific, the parameters were not defined automatically, but empirically following a trial and error process. Systematic error additionally comes from the remote sensgin system that may degrade the research quality. Further study is thus needed to develop a new method that is robust to the types of images used and their corresponding parameters.

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