

DETERMINATION OF LARGE-SCALE DIGITAL ELEVATION MODEL IN WOODED AREA WITH AIRBORNE LIDAR DATA BY APPLYING ADAPTIVE QUADTREE-BASED ITERATIVE FILTERING METHOD

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ABSTRACT:

Generation of large-scale digital elevation (or terrain) models of wooded areas is fundamental to LIDAR data's application in forest management to a large extent. In this paper, a new method is proposed and implemented, which is characterized by its combination of adaptive quadtree-based processing with common iterative interpolation and filtering methods. Digital elevation models (DEM) of wooded and undulating hill areas are derived from airborne LIDAR data, and they have proved to be in good accordance with field survey data of terrain surfaces, collected by high-precision total-station. Also, good efficiency of adaptive quadtree-based iterative filtering algorithm was verified as well as its adaptation for processing high density LIDAR data over a large extent.

1. INTRODUCTION

Acquirement of digital elevation model (DEM) is essential for forest management. The airborne laser imaging detection and ranging (LIDAR) technology provides a revolutionizing way to acquire a high-resolution DEM by allowing rapid and inexpensive measurements of topography over a large area. LIDAR system produces 3D measured point data, which is sub-randomly distributed. LIDAR also has the ability of penetrating the canopy by collecting reflections from canopy and understory. In order to generate DEM, measurements from ground and non-ground features have to be identified and classified. Removing non-ground measurements from LIDAR dataset has proven to be a key technology, especially in forest measurement and management.

Vosselman proposed a slope-based filter (Vosselman, G., 2000) that identifies ground measurements by comparing slopes between a LIDAR measurement (point) and its neighbors. A point is classified as a ground measurement if the maximum value of slopes between this point and any other point within a given circle is less than a predefined threshold. The lower the threshold slope, the more objects will be removed. A reasonable threshold slope can be obtained by using prior knowledge about terrain in the study area.

The implicit premise of applying the slope-based filter is that there is a distinct difference between the slope of terrain and that of non-ground objects such as trees and buildings. Satisfactory results have been achieved in experiments by applying the slope-based filter to flat urban areas. However, the filtering of measurements on vegetated mountain areas with a large slope variation cannot be perfect, and errors are generated within the derived DEM.

Axelsson developed a filtering algorithm based on Triangular Irregular Networks (TIN) (Axelsson, P., 2000.) to eliminate measurements not belonging to the ground surface from the original return points. First, seed ground points within a user-

defined grid of a size greater than the largest non-ground features are elected to compose an initial ground dataset. Then, one point above each TIN facet is added to the ground dataset every iteration if its parameters are below threshold values. The iteration continues until no points can be added to the ground dataset. The problem with the adaptive TIN method is that different thresholds have to be given for various land cover types.

Kraus and Pfeifer utilized linear least squares interpolation iteratively (Kraus K, Pfeifer N., 1998) to remove tree measurements and generate DEM in forest area. In the first step, a surface is computed with equal weights for all points, which runs in an averaging way between terrain points and vegetation points along the altitude direction. The terrain points are more likely to have negative residuals, whereas the vegetation points are more likely to have small negative or positive residuals. These residuals are used to compute weights for each point. In the next step, the points with large negative residuals have maximum weights and they attract the computed surface, whereas points with medium residuals have smaller weights and less influence on the computed surface. Points with larger positive residuals are eliminated and other points with smaller residuals are reserved for the next iterative. By repeating the above process, surface approximated to the actual ground surface is generated iteratively, which leads to final determination of ground return points. However, it is difficult to detect the various terrains' non-ground points completely using Kraus's method, and a large amount of CPU time is required to process high density LIDAR data over large areas.

Considering the computational complexity of the above algorithms, and their infeasibility in the case of high density LIDAR, a non-overlapping segmentation method, quadtree-based iterative filtering algorithm was proposed in this paper, which aims to remove non-ground measurements from the LIDAR dataset in wooded areas, in order to generate large scale DEM with reasonable efficiency.

2. QUADTREE-BASED ITERATIVE FILTERING ALGORITHM

The quadtree-based iterative filtering algorithm is based on Kraus's iterative filtering algorithm (Kraus K, Pfeifer N., 1998) and quadtree segmentation algorithm (Finkel, R. A., 1974).

The initial step is to divide the LIDAR data into a grid network on two (x, y) dimensional space. See Figure 1-(a) for detailed description of initial square unit region (board size = n meters).

Secondly, Kraus's filtering is performed within each initial square unit to remove non-ground points for the first time. And statistics on the leftover points will provide the following statistic parameters for the next process;

- (1) Number of left LIDAR points
- (2) Residuals of left LIDAR points to derived average surface along with altitude direction.

Based on the above indices, initial unit regions could be separated into four quadrants (sub-regions, board size = n/2 meters) under certain conditions. In this study, conditions are designed as below.

Condition 1: Number of left LIDAR points is more than the given threshold (T_A in Figure 2).

Condition 2: Mean of residuals is more than the given threshold (T_B in Figure 2).

In the next step, quadtree segmentation will be performed within initial unit regions, which will meet the above conditions. See Figure 1-(b).

The above processes are performed repeatedly through the whole region of data, with results shown in Figure 1-(c), (d).

According to the flowchart of LIDAR data processing in this study (Figure 2), the DEM is finally generated from TIN, which is composed of ground points extracted out of LIDAR data.

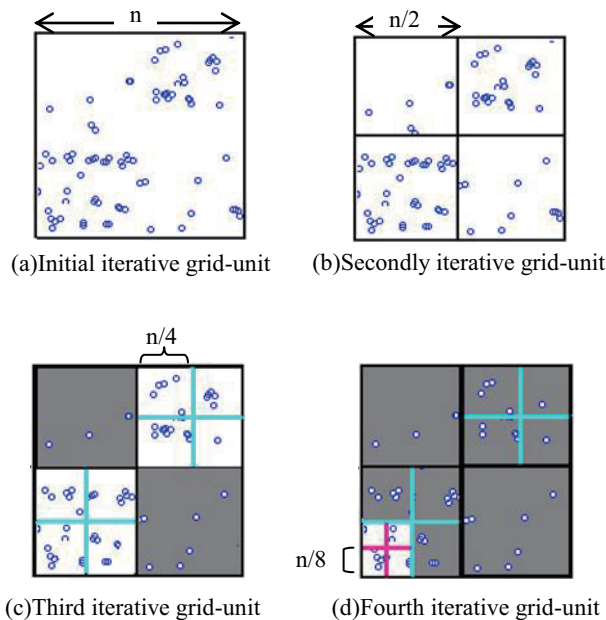


Figure 1. Process of iterative quadtree segmentation

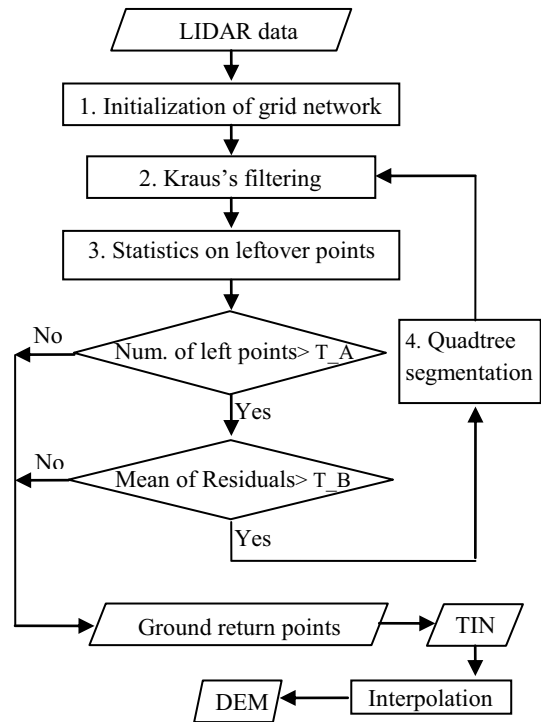


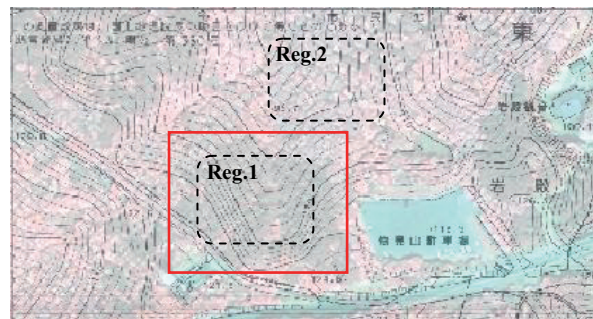
Figure 2. Flow chart of the LIDAR data's processing.

3. EXPERIMENTS

3.1 Study Area

This paper's study area is located in undulating hill covered by second-growth forest, which is mainly composed of *Quercus serrata* (deciduous broad-leaf), *Pinus densiflora* (conifer). Within the study area, terrain slope varies between 0~60 degrees, with elevation variation up to 75.51 meters.

In the study area, understory was cut in rotation among the sub-regions, and the interval is about 5 years. Between Region No.1 and No.2 in Figure 3, the status of understory management is different. At the time of LIDAR measurement and field survey, understory in Region No.1 was clearly cut (managed area), while Region No.2 was untouched (unmanaged area). In this paper, Region No.1 in Figure 3 was selected as the test site.



* Composition of Terrain Map and IKONOS colour Image
Legend [Study area] [Sample region]

Figure 3. Overview of study area (Iwadono Forest Park, Higashi-matsuyama City, Saitama Pref.)

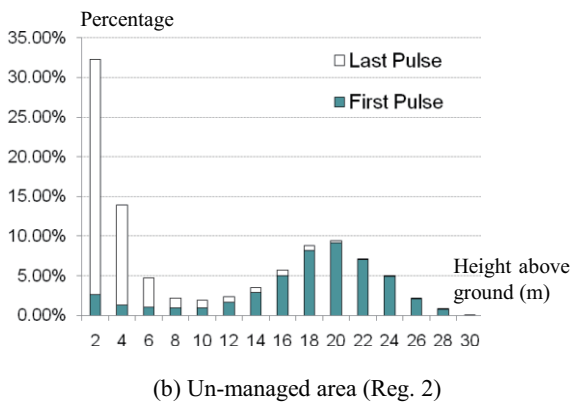
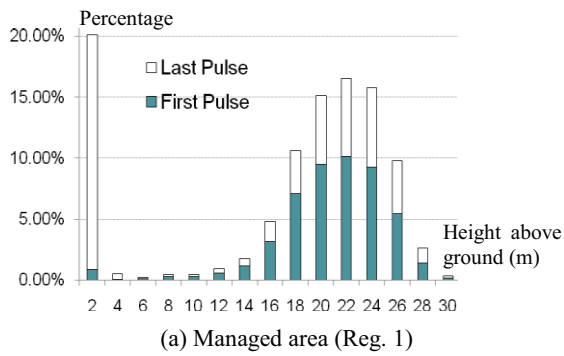


Figure 4. Histogram of LIDAR data of regions with different understory management status

3.2 LIDAR data

The LIDAR data of study area was collected by an airborne LIDAR mapping system mounted to a Cessna 404 aircraft on the 25th of December, 2006. The collected LIDAR data includes two returns for each laser pulse, which were assigned with names of “first pulse” and “last pulse” according to reception sequence. Each measurement contains attributes of its 3D location (x, y, z) only. There is no record of reflection intensity of the return pulse, and average point density was about 3.4 points/m².

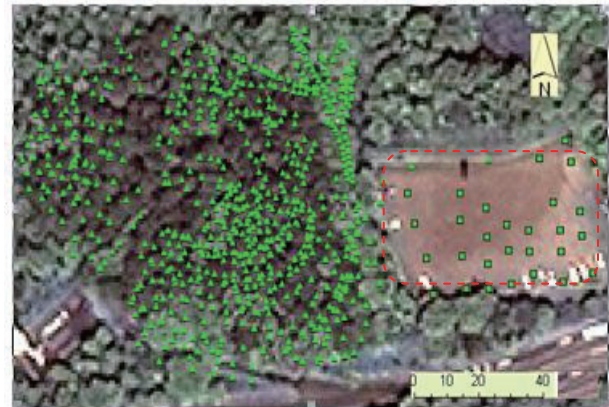
Detailed specifications of above airborne LIDAR are shown in Table 1.

Item	Description
Average point density	3.4/m ²
Laser Pulse Frequency	65kHz
Off-nadir Scan Angle	+/-18 deg.
Scan Frequency	45Hz
Altitude of flight	1200m
Speed of flight	252 km/h
Overlay between flight lines	40%
Interval between flight lines	180m
Airborne platform	Cessna Titan
Divergence full angle	0.3mrad
Attribute item of measurement	X, Y ,Z
Type of return pulse	Last pulse / first pulse

Table 1. Specifications of Airborne LIDAR

3.3 TS measurement

In this study, total station (TS) was used to collect reference data for assessing the accuracy of the LIDAR-derived DEM. The collected terrain survey data (587 points) is shown in Figure 5.



▲ TS points (within woods) ■ TS points (within park)

Figure 5. Distribution of TS measurements

3.4 Data Calibration

Before data processing, data calibration was firstly performed to remove systematic error between airborne LIDAR data and TS measurements, by using TS measurement within a car park (Figure 5) near the test site. Mean value of altitude difference between TS measurements and LIDAR points (within radius of 0.5 meters) was derived (about 32cm, see Table 2), which is used as system error correction value of Airborne LIDAR data.

Statistic Target	Mean value of elevation (m)		Diff. of Elevation (m)
TS points	TS	LIDAR	$Z_{LIDAR} - Z_{TS}$
Total 34	119.549	119.223	-0.327

Table 2. Result of the data calibration

3.5 Results of data processing

Intermediate and final outcomes of LIDAR data’s processing are shown in Figure 6. In Figure 6(a), in which is shown the shaded relief image of original LIDAR measurements. Below observing sites were selected for visual check.

Check site 1, which is located outside of the study area and occupied by dense herbaceous plant.

Check site 2, which is located in the study area and is covered by the second-growth woods.

Check site 3, which contains under-wood road.

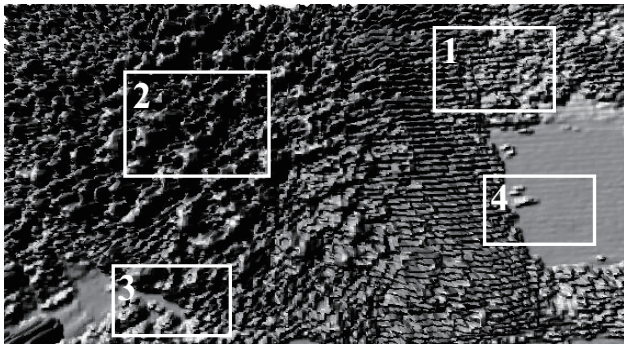
Check site 4, which is located in the car parking lot.

As shown in Figure 6(d), the final outcome could be visually confirmed at the above check sites. Detailed descriptions are as follows.

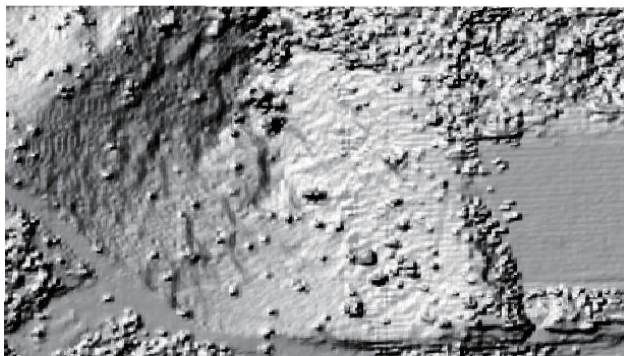
At check site 1 and 2, return points of woods, as well as herbaceous plant, were almost removed.

At check site 3, under-wood road was discovered with clear shape.

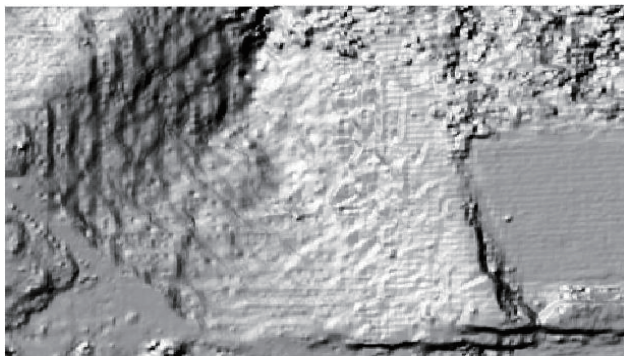
And at check site 4, it could be seen that return points of cars in the park were removed. Also, steep slope along with the terrain boundary was correctly discovered.



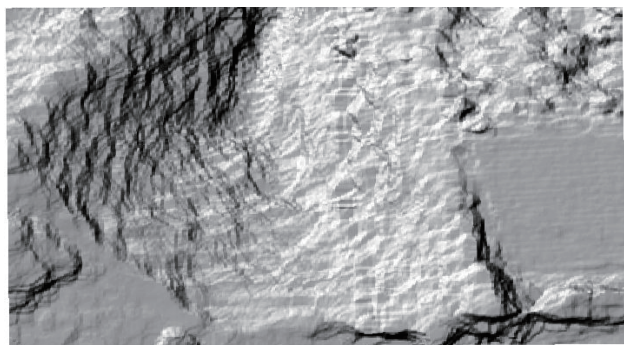
(a) Shaded surface of Original LIDAR points



(b) Shaded surface of leftover LIDAR points after first filtering process



(c) Shaded surface of leftover LIDAR points after second filtering process



(d) Shaded surface of ground return points

Figure 6. Outcome of LIDAR data's processing

Profiles of LIDAR data along with derived ground return points are shown below in Figure 7. It was revealed that non-ground return points were removed successfully by the quadtree-based iterative filtering algorithm proposed in this study (see Figure 7 (b), (c)).

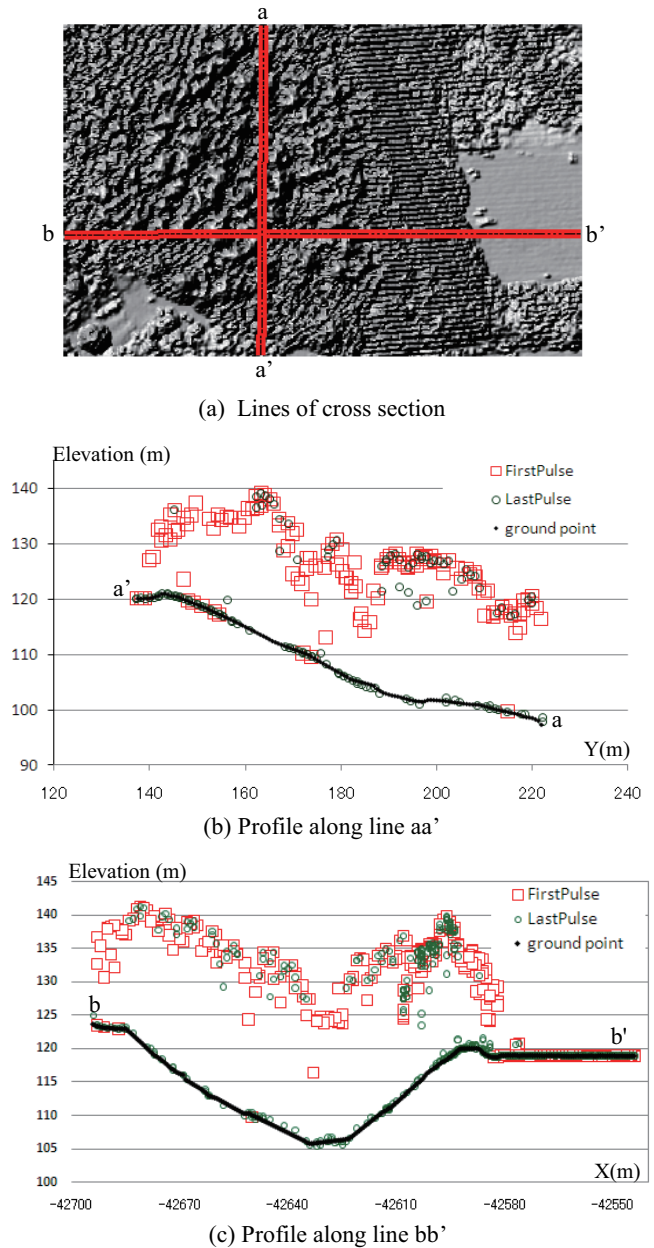


Figure 7. Profiles of LIDAR points and ground-return points

4. DISCUSSIONS

4.1 Determining of DEM's grid size

Concerning spatial resolution of DEM, RMSE of DEM generated with different grid sizes was calculated and compared. As shown in Figure 8, by taking TS measurement as reference data, RMSE of DEMs with grid sizes ranging from 0.25m to 12.5m were derived, which varied from 0.413m to 0.695m. The grid size with the lowest RMSE was found to be 1 m, and it was adopted for generating the final DEM.

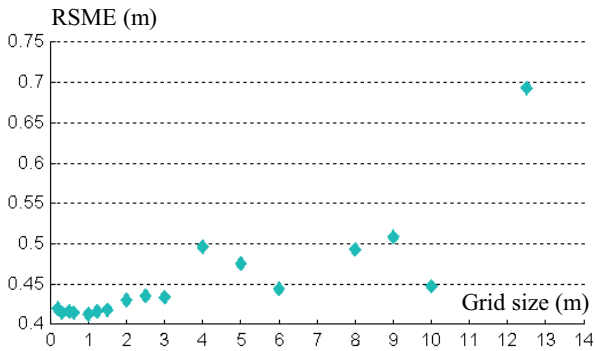


Figure 8. RSME of DEM with different grid size

4.2 Error of DEM

By using TS measurement (587 points) as reference data, (altitude) error of DEM (grid size = 1m) was summarized, with error histogram shown in Figure 9. According to the histogram, the majority (approximately 98.5 per cent) of errors of the Z values are between -1m and 1m, and of these, around 78.5 per cent are within range [-0.5m, 0.5m].

With RMSE(Z) of 0.413m and STD(Z) of 0.396m, it was cleared that derived DEM meet the requirements of national cartography standard on large-scale terrain mapping. For example, the national standard for terrain map with scale of 1/2500 is $STD_z \in [-0.66m, 0.66m]$.

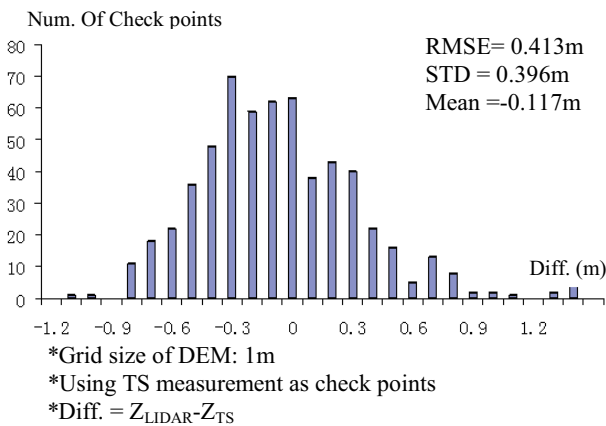


Figure 9. Error Histogram of DEM

4.3 CPU Time

Along with a high accuracy of DEM generation, the proposed quadtree-based iterative filtering algorithm also proved to have higher data-processing efficiency when compared to the original algorithm. As shown in Table 3, compared with Kraus’s algorithm, the quadtree-based iterative filtering algorithm has great advantages in CPU time, as well as DEM accuracy.

Comparing Items	Quadtree-based iterative filtering algorithm	Kraus’s algorithm
CPU time (s)	59.22	88.87
RMSE (m)	0.413	1.7034

Table 3. The comparison results of the Quadtree-based iterative filtering algorithm and the Kraus’s algorithm

5. SUMMARY

In this paper, a new method is proposed and implemented, which is characterized by its combination of adaptive quadtree-based processing with common iterative interpolation and filtering method. Digital elevation model (DEM) in wooded and undulating hill area was derived from airborne LIDAR data, and it was proved to meet the requirements of national cartography standard on terrain mapping with large scale up to 1/2500. Also, good efficiency of adaptive quadtree-based iterative filtering algorithm was verified as well as its adaptation for processing high dense LIDAR data over a large extent.

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