ASSESSING THE POSSIBILITY OF LAND-COVER CLASSIFICATION USING LIDAR INTENSITY DATA

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ABSTRACT:

LiDAR (Light Detection and Ranging) is widely used in such fields as Digital Surface Model (DSM) production. It provides intensity data that reflect the material characteristics of objects, so it is possible that intensity data could be used for land-cover classification.
In this study, we assessed the possibility of land-cover classification using LiDAR intensity data instead of the multi-spectral data that has commonly been used for classification. We converted LiDAR point data to a grid and assessed the separability of intensity data on some classes, including asphalt road, grass, house roofs, and trees. However, the grid data was very noisy because of errors during data acquisition or from the resampling processes. To solve this problem, we examined some resampling and filtering methods that can remove noise effectively while the original information is preserved as much as possible.
From this study, we concluded that LiDAR intensity data could be used for land-cover classification.

1. RESEARCH BACKGROUND AND OBJECT

Since the Light Detection and Ranging (LiDAR) technique with high vertical accuracy was developed, LiDAR has been used in such fields as Digital Surface Model (DSM) production, extraction building, and 3D city modeling. Research on land-cover classification has also used DSMs extracted from LiDAR. Norbert Haala and Claus Brenner (1998) accomplished classification using DSM and CIR (Color Infra Red) images. Hans Gerd Maas (1999) classified land cover using textures extracted from DSM that indicated height, roughness, maximum inclination, and so on.
LiDAR provides both height data and intensity data that reflect material characteristics of objects. In this study, we assessed the separability of LiDAR intensities for four classes: asphalt road, grass, house roofs, and trees, and evaluated the possibility of land-cover classification using LiDAR intensities.

2. LIDAR SYSTEM

2.1 LiDAR System

A laser system is almost free from intervening air effects, because laser light travels in straight lines and has strong penetration with small Instantaneous Field Of View (IFOV). Further, because the laser scanner is an active sensor that emits light and measures reflected light, it does not require sunlight. Generally, the wave length of lasers used for LiDAR is 0.9 ㎛, and a LiDAR system has the high accuracy of 30 ㎝ vertically and 15 ㎝ horizontally. LiDAR systems are usually called Laser Detection and Ranging (LADAR) or Airborne Laser Scanners (ALS).

LiDAR altimetry uses the laser scanner, a GPS receiver, and an Inertial Navigation System (INS) including IMU (Inertial Measurement Unit). The laser scanner can be considered as separate operations of distance measurement and scanning, which are integrated and operated by a controller. There are also additional components such as data storage media, a ground GPS receiver, data processing software, and a navigation system.

2.2 LiDAR Intensity

Intensity is defined as the ratio of strength of reflected light to that of emitted light, and is influenced mainly by the reflectance of the reflecting object. Reflectance varies with material characteristics as well as the light used, and different materials have different reflectances. Consequently intensities may be useful information for classifying land cover.
Table 1 shows intensities of various materials for 0.9 ㎛ lasers. This wavelength belongs in the infra-red, and intensities of 0.9 ㎛ infra-red ray are also shown in Figure 1.
Of the four classes in this study, 'asphalt' has the intensity value of 10%~20%, 'grass' about 50%, 'tree' 30%~60%, and 'house roof' of 20% (for shingle)~30% (for concrete). Thus, each class has a different intensity and separability can be established.

Materials	Reflectivity(%)
White paper	Up to 100
Dimension lumber	94
Snow	80~90
Beer foam	88
White masonry	85
Limestone, clay	Up to 75

Newspaper with print	69
Tissue paper, with ply	60
Deciduous trees	Typ. 60
Carbonate sand(dry)	57
Beach sands	Typ. 50
Carbonate sand(wet)	41
Coniferous trees	Typ. 30
Rough wood pallet (clean)	25
Concrete, smooth	24
Asphalt with pebbles	17
Lava	8
Black rubber tire wall	2

Table 1. Reflectivity of 0.9 μm Laser (company Riegl)

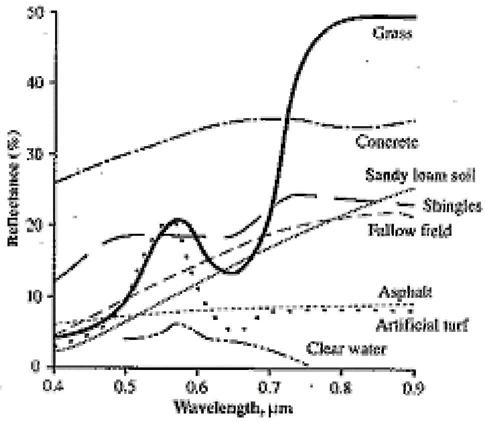

Figure 1. Reflectivity of Various Wave Length of Infra-red (Jensen, 1989)

However, LiDAR intensity data are very noisy and possibly have low separability if the wavelength of the laser used is not suitable for the materials. The main source of intensity noise is the angle of reflection, as some materials have different intensity values as the angle of reflection varies. Therefore, to make intensity represent only reflectance and not be affected by reflection angle, it is necessary to normalize intensity data by the angle of reflection. In this study, however, this was not accomplished because of the lack of ALS orientation information.

3. INSTENSITY PROCESSING

3.1 Conversion Point Data to Grid

Generally, as LiDAR data are provided in the form of point data, it is necessary to convert the data to grid form. In this study, we used the Inverse Distance Weight (IDW) and the Kriging interpolation methods. Kriging is a set of linear regression routines which minimize estimation variance from a predefined covariance model.

3.2 Filtering the Grid Data

A LiDAR intensity grid, especially one generated using the IDW method, includes much ‘salt and pepper’ noise, with values that vary even inside the same feature. The origin of this noise can be thought of as grid conversion error or systematic or accidental errors in surveying. The systematic and accidental errors are specified as forms of vertical position error, which can be generated from GPS, distance measurements or IMU. Similar reasoning can be applied to horizontal errors (B.K. Lee, 2001). The sizes of systematic and accidental errors are affected by the type of land-cover and the magnitude of the slope. According to Huising and Gomes Pereira (1998), each error can be of magnitude 5~20 ㎝ for some land-cover types, and as much as 20~200 ㎝ on grassland, copses or sloping land. Therefore the noise on the intensity grid can be the result of incorrect surveying because of the above errors. To remove noise from the images, mean filters or median filters are usually used. The median filter serves to reduce pixel value distortion, preserving the feature boundary and effectively softening rough surfaces. The ‘salt and pepper’ noise must be removed, and some rough surfaces should be made homogeneous because they can have a negative influence on the accuracy of classification and the shape of the classified feature.

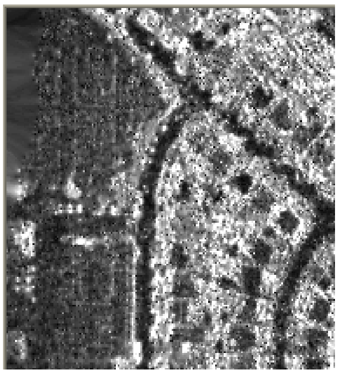

Figure 2. Original Intensity Grid (IDW)

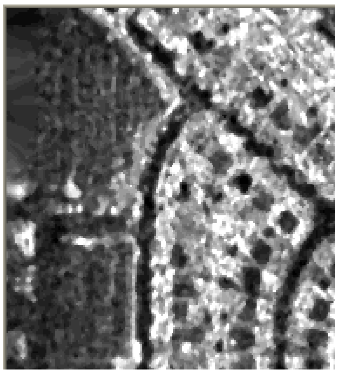

Figure 3. 3 x 3 Median Filter Applied to the Intensity Grid

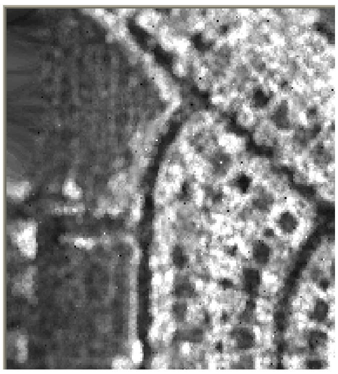

Figure 4. Intensity Grid (Kriging)

Figure 2 is an original intensity grid interpolated by the IDW method and Figure 3 is the intensity grid after applying a 3×3 median filter. Figure 4 is the intensity grid interpolated using the Kriging method. It has little ‘salt and pepper’ noise and resembles Figure 3 because of the characteristic smoothing effect of the Kriging method.

4. EVALUATION

4.1 Data Specification

Table 2 shows details of the LiDAR data of this study. As training data for signature analysis, we used ortho-rectified black and white aerial digital images.

Data Components	x , y Coordination, Height, Range, Intensity
No. of Points	660□425
Average of Point Distance	0.602m
Average of Intensity	44.736
Standard Deviation of Intensity	11.216
Coordinate System	UTM WGS84 north zone 11

Table 2. LiDAR Data in Study

4.2 Intensity Analysis

Table 3 shows the statistics of intensity data interpolated using the IDW method, and shows that the variance of intensity is diminished by median filtering.

Class	Average		Deviation	
	Before Filtering	After Filtering	Before Filtering	After Filtering
Asphalt	35.197	35.178	2.125	1.604
Grass	47.115	47.052	4.841	3.655
Roof	38.409	38.335	4.348	3.697
Tree	50.288	49.987	7.234	4.709

Table 3. Statistics of the Intensity Grid (IDW)

The intensities for ‘asphalt road’ and ‘house roof’ are larger than the expected 10%~20%.

The reasons for the larger intensity estimations can be stated as follows. First, the wavelength of the laser in this study is different from that used in Table 1. Second, the compositions of real materials are more complex than those of laboratory references, and poor estimates of intensity could be caused by various error factors in the surveying step. Finally, the objects may be composed of materials that cannot be recognized by the black and white reference image.

‘House roof’ has similar intensity to ‘asphalt road’. This probably occurs because asphalt shingle is used widely as a roofing material. Asphalt shingle is an asphalt-coated building material to withstand weathering. From the reference image, many house roofs are seen to be made of asphalt shingle (Figures 5 and 6).

Figure 5. 'Asphalt Shingle' as Roof Material

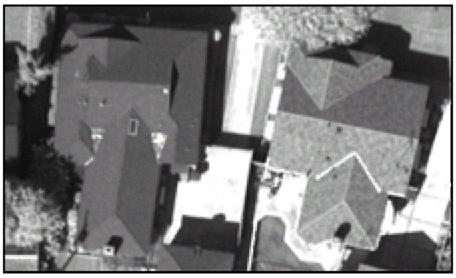

Figure 6. Roofs in the Study Area

The estimated intensity for ‘grass’ is about 50%, and also for ‘tree’. The variance for ‘tree’ is higher than other classes, possibly because intensity varies with the kind of tree and the shape of leaf. For example, the intensity of a conifer is about 30% while that of a broadleaf tree is usually 60%.

4.3 Separability Assessment of Intensity

To assess the separability of intensities, a transformed divergency method was used. This is a modified divergency method that allows users to easily interpret the separability. It is possible to obtain relative separabilities between classes by the divergency method, but the resulting values do not indicate the absolute separability, to consider whether real classification is possible. The transformed divergency method represents the separability in the range 0~2000 and one can estimate the separability level (Table 4).

$$D_{ij} = \frac{1}{2} tr\{(C_i - C_j)(C_i^{-1} - C_j^{-1})\} + \frac{1}{2} tr\{(C_i^{-1} - C_j^{-1})(\mu_i - \mu_j)^T\}$$

$$TD_{ij} = 2000\{1 - \exp(\frac{-D_{ij}}{8})\}$$

where i, j : comparison classes

C_i, C_j : covariance matrix of class i, j

μ_i, μ_j : average vector of class i, j

tr : trace function

TD	Level of Separability
Up to 1900	Excellent
1700~1900	Good
~1700	Poor

Table 4. The Level of Separablity for Assessment

We assessed separability of intensity on three intensity grids: interpolated with the IDW method, median filtered, and interpolated with the Kriging method. The results are as follows.

	Asphalt Road	Grass	House Roof	Tree
Asphalt Road	0	1844.83	560.05	1964.43
Grass	1844.83	0	731.8841	156.43
House Roof	560.05	731.88	0	1012.44
Tree	1964.43	156.43	1012.44	0

Table 5. Separability of Intensity (IDW)

	Asphalt Road	Grass	House Roof	Tree
Asphalt Road	0	1972.70	794.368	1996.55
Grass	1972.70	0	1009.79	155.51
House Roof	794.37	1009.79	0	1277.70
Tree	1996.55	155.51	1277.7	0

Table 6. Separability of Intensity (IDW, median filtered)

	Asphalt Road	Grass	House Roof	Tree
Asphalt Road	0	1986.67	945.75	1997.94
Grass	1986.67	0	1026.01	106.75
House Roof	945.75	1026.01	0	1244.14
Tree	1997.94	106.75	1244.14	0

Table 7. Separability of Intensity (Kriging)

Separabilities for 'asphalt road' vs. 'grass' and 'asphalt road' vs. 'tree' are rather high, 'house roof' vs. 'tree' are medium, and 'asphalt road' vs. 'house roof' and 'grass' vs. 'tree' are very low (Table 5). This result could be expected from the above intensity analysis. If DSM is added to the classification process, 'asphalt road' vs. 'house roof' and 'grass' vs. 'tree' will be classified because they have different heights.
In Table 6 and Table 7, it can be seen that filtering and other interpolation methods enhance separability. In particular, very high separabilities are obtained between 'asphalt road' and 'house roof', and 'grass' and 'tree'.

5. CONCLUSION

This study is intended to evaluate the suitability of LiDAR intensity data for land-cover classification. We converted LiDAR point data to grid form using two interpolation methods and filtering, and assessed the separability of intensity data on four classes: asphalt road, grass, house roof, and tree.
The conclusions are as follows.
First, while LiDAR intensity does not exactly conform to theoretical reflectances of materials, it does follow relative magnitudes of reflectance, thus permitting separability. Therefore LiDAR intensity can be used for land-cover classification.
Second, LiDAR intensities and the intensity grid contain much noise originating from various sources. To enhance separability of intensity, adequate methods of interpolation and filtering must be applied.
Third, LiDAR is a very cost-effective and accurate surveying technology because position and intensity data for the same site can be estimated simultaneously.
Fourth, as more processing, such as normalization, and DSM are added, LiDAR intensity will have the potential to identify more classes.
Advanced research subjects include intensity normalization using orientation information from ALS, and the development of more adequate interpolation and filtering methods for the intensity grid.

REFERENCES

1) Hans Gerd Maas, 1999, The Potential of Height Texture Measures for the Segmentation of Airborne Laser scanner Data, 4*th Internat. Airborne Remote Sensing Conference & Exhibition*.

2) Aloysius Wehr, and Uwe Lohr, 1999, Airborne Laser Scanning - an Introduction and Overview, *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 54, pp. 68–82.

3) Lee Byung kil, 2001, Geometric Corrections for Airborne Laser Mapping Data in the Generation of Large Scale DSM, *Seoul National Univ.*

4) G. Priestnall, J. Jaafar, and A. Duncan, 2000, Extraction of Urban Features from LiDAR Digital Surface Models, *Computers, Environment & Urban Systems*, Vol. 24, pp. 65–78.

5) Norbert Haala, and Claus Brenner, 1999, Extraction of Buildings and Trees in Urban Environments, *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 54, pp. 130–137.

6) Bettina Petzold, Peter Reiss, and Wolfgang Stossel, 1999, Laser Scanning - Surveying and Mapping Agencies are Using a New Technique for the Derivation of Digital Terrain Models, *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 54, pp. 95–104.