LiDAR SIGNATURES TO UPDATE JAPANESE BUILDING INVENTORY DATABASE

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ABSTRACT

Developing an efficient method to quickly update the building inventory database of dense urban areas is our focus of interest. Disaster mitigation requires an up-to-date and reliable building inventory database for damage assessment. However, it has been slowly updated through conventional procedure comprising the compiling aerial photographs, manually or semi-automatic updating GIS database and manually inputting attributes from submitted documents. LiDAR providing very dense point clouds with X, Y, Z coordinates and pulse intensity is proposed as primary data for a better flowchart of updating. This study developed a comprehensive method to detect and classify the buildings from LiDAR data based on sizes and height. Testing with data acquired over Roppongi area of Tokyo, Japan demonstrated the capability of the proposed method. It inferred that promising results derived by an automatic processing LiDAR data seems to be a better solution to update building inventory database in dense urban areas. Elevation and intensity distribution of the laser points will be integrated in further improvement.

1. INTRODUCTION

LiDAR theory is well-understood (Wehr and Lohr, 1999). It has been widely used in topographic mapping for many disciplines. While the development of LiDAR sensor has become a mature technology, LiDAR post-processing is still under-developed. The existing algorithms are not fully reliable (Dowman, 2004). Focused algorithms include extraction of the bare-earth (Sithole and Vosselman, 2004) and building reconstruction for 3D city modeling such as Maas and Vosselman (1999) and many others. On the other hand, there is also a current trend to develop three-dimensional database in which LiDAR is concerned as potential acquired data. Olsen (2004) and Walter (2004) employed LiDAR in assisting the change detection and then, updating TOP10DK and ATKIS database map, respectively. Those researches were different in map scale but both relied on spectral information and used height information from LiDAR for verification only. However, Olsen (2004) also stated that spectral information of building is diverse and ill-defined. Not only the diversity of spectral information but also the difficulties in ortho-rectifying the aerial photographs slows down the process of map updating. This problem becomes critical in very dense urban areas like Japan's. Therefore, we proposed the usage of LiDAR as primary data in map updating in which LiDAR located the hot-spots of changes and those changes were consequently verified by supplemental spectral information. Previous attempts were matching LiDAR and GIS database (Vu el al, 2004a) and LiDAR-based change detection (Vu el al, 2004b). The next step is to classify the buildings based on LiDAR signatures. A part of this work is the content of this paper. Following section describes the methodology of LiDAR-based classification and is followed by its demonstrated testing.

2. METHODOLOGY

Reflected LiDAR pulses commonly form the Earth's surface model, called Digital Surface Model (DSM). But many applications require the bare-earth model (Digital Terrain Model or DTM) rather than that DSM. Thus, classifying the laser points into off-terrain points and terrain points is always the first step, which is also called filtering. In this study, we applied the wavelet-based method (Vu and Tokunaga, 2004). The difference between the surface model and the bare-earth model presents the heights of overlaying objects. It can be called Digital Height Model (DHM) to distinguish it from DSM and DTM. LiDAR provides very dense point clouds with X, Y and Z coordinates, it is applicable to classify the buildings based on their sizes and heights from that point clouds. It is noted that DHM are stored in both grid-based and point-based formats. To speed up the classification processing, the grid-based format is preferred.

The image classification is the basic and main task in processing remotely sensed imagery. Conventional methods, supervised or unsupervised classification, are mostly pixel-based and fix scale processing. As a result, intra-object error in classification is the big problem and objects are smashed into the fragments. Scale-space theory (Lindeberg, 1998) and object-based classification have been taken into account in image classification (Hay et al, 2002). Moreover, non-linear scale space has been proposed in classification (Acton and Mukherjee, 2000). Non-linear scale space classification based on area morphology showed very good results in classification and forming the objects. In classification of DHM image, we applied this non-linear scale space scheme with our approximate implementation based on morphological opening and reconstruction (Vincent, 1993). Detailed processing is described step-by-step as follows.

Prior to the scale space analysis, it is necessary to find the range of scales to be analyzed. Giving the minimum and maximum bounds and the sampling intervals of the scale space, the computational complexity of the scale space analysis is reduced. This range can be observed from the distribution of the object's size, which can be extracted by the granulometry analysis (Matheron, 1975). Therefore, granulometry is employed here to determine the range of scales.

As mentioned above, non-linear scale space is based on area morphology. The basic idea of opening area morphology $S \circ s$ is the removal of all components of area less than s in the set S where $\circ$ stands for opening operator (Acton and Mukherjee, 2000). Different from the basic opening morphology, an area operator is amorphous. It is useful to classify the objects across the scale space without rounding the object's corner, and hence, without loosing the object's details. The drawback of this method is time consuming. The approximate implementation based on morphological opening and reconstruction (Vincent, 1993) shows much faster computation. Let call an original image is *MASK I* and that opening filtered is *MASKER J*. The reconstruction of $\rho_I(J)$ of *MASK I* from *MARKER J* is the union of the connected components that contain at least one pixel of *J*. The opening operator used here is basic cross-shapes or flat kernel with increased sizes according to the chosen range of scales. Figure 1 demonstrates the results of 5x5 flat-kernel opening and area morphology filtering. The result of the non-linear scale space analysis of DHM is the classes of objects based on their sizes and heights.

a) **b)** **c)**

Figure 1. Demonstration of morphological filtering: a) original image, b) 5x5 flat-kernel opening and c) area morphological opening with area of 25.

However, trees and bushes still remain in the classified objects. It is possible to remove them from buildings and other man-made objects using NDVI which requires spectral information of Red and Near-Infrared bands. Fortunately, current LiDAR surveying flights record the intensity of reflected pulses which are about 900-1050 nm belonging in the infrared. Those flights also equip a digital camera to acquire color aerial photographs. We simulate the near-infrared channel from this pulse intensity and incorporate it with Red channel of aerial photograph to compute NDVI. The simple thresholding of NDVI can discriminate between vegetation and others.

Finally, classified blobs based upon object's sizes and heights are used as the mask to group the laser points. Depending on each study area, the number of class is various. Normally, it is about 4-6. There are also other classes such as ground, vegetation as the results of classification. It should be noted that laser points can be reflected from the walls of the buildings. When being considered all of X, Y, and Z coordinates, those points can cause ambiguity between classes. Furthermore, to prepare for a further analysis of distribution of elevation and intensity of laser points on the roof of buildings, those points should not be concerned. We mark the overlapped points as a separate class.

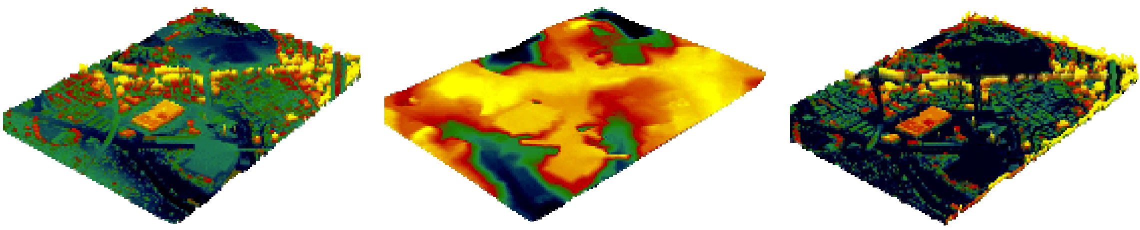
3. TEST RESULTS AND DISCUSSION

A LiDAR data set acquired over Roppongi, Tokyo, Japan was chosen for testing. Table 1 shows the parameters of the surveying flight. DSM, DTM and DHM, which are all in 1-meter grid format, are presented in Figure 2. Trees can be observed on the left and upper right part of the scene and several others interspersed between the buildings. After classification of laser point clouds to obtain DTM, elevated roads were categorized as long overlying objects, e.g. the elevated expressway at the bottom right of the scene. This classification produced a DTM with RMSE about 1.1 meters when compared to ground control points. It also flattened some small underground spaces next to the buildings, which produced the negative values in DHM. Those small spikes were not our concerned. They were reassigned to be 0 meter as ground. The classification using the non-linear scale space analysis produced the classified buildings as in

Figure 3. The simulated image using the pulse intensity and color aerial photograph and the computed NDVI image are shown in Figure 4.

Table 1. Parameters of surveying flight

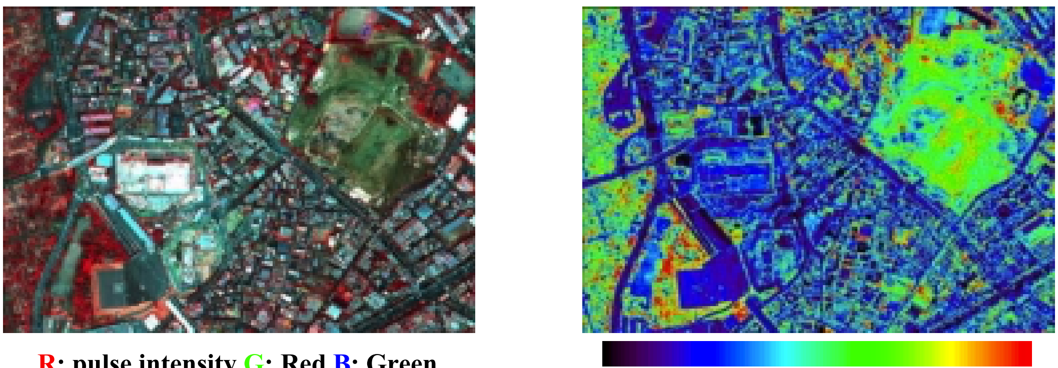
Flight altitude	1000m
Flight speed	250 km/h
Pulse frequency	30 KHz
Scan frequency	39 Hz
Field-of-view	$\pm 10^0$
Strip overlap	50%
Point spacing	≈ 0.9 m
Wavelength	1064 nm



a) **b)** **c)**

Figure 2. Test area: a) DSM, b) DTM and c) DHM.

Figure 3. Results of non-linear scale space analysis



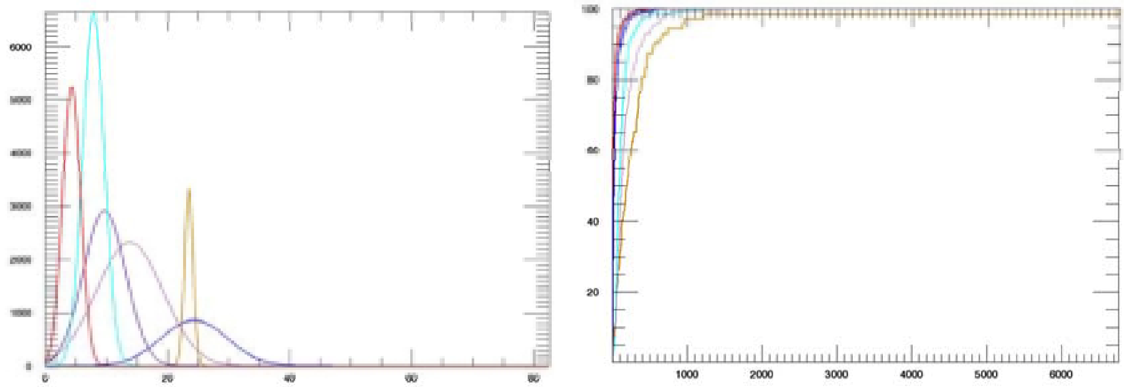
R: pulse intensity G: Red B: Green

Low **High**

a) **b)**

Figure 4. a) Simulated false color composite; b) NDVI

Finally, laser points were classified into 6 classes according to their heights and sizes. Elevation distribution of each class is demonstrated in Figure 5a and its size distribution is demonstrated in Figure 5b for reference. As observed in Figure 5, objects were classified somehow into low-rise and high-rise groups and their sizes assisted the further classification into 6 classes.



a) **b)**

Figure 5. a) Elevation distribution and b) Size distribution.

There were several steps in the proposed methodology many of which were fully automated. However, the proposed method allowed a limited amount of human interaction with the processing to assure the reliable results. The step that needs human interaction was firstly the decision making of the range of scales by observing the histogram of granulometry. Secondly, it was the decision for NDVI threshold. Computational time of the automated processing only depended on the range of scales, i.e. upon on the scene, and density of laser points, i.e. upon acquired data.

4. CONCLUSION

Employing LiDAR as primary data in map updating could increase the level of automation. Hence, it is promising to speed up the process of map updating and produce higher reliable results. That is the main contribution of this study. In addition, non-linear scale space processing was also proposed and successfully implemented. This paper focuses only sizes and heights of buildings in classification but it was well-prepared and opened to integrate elevation and intensity distribution in further studies.

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