DTM Generation and Buildings Detection Using LIDAR Data

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Abstract: In this paper we propose a scheme to generate DTM and detect buildings on DSM generated from LIDAR data. Two stages are performed. The first stage is to perform object segmentation by using two morphology operations namely, flattening and H-Dome transformation. After filtering out the object points above the ground, we used the non-object points to generate DTM. The second stage is to detect buildings from the objects by analyzing differential slopes. The test data is in raster form with 1m spacing around Hsin-Chu Scientific Area in Taiwan. The mean error is -0.16m and the RMSE is 0.45m for DTM generation. The successful rate for building detection is 87.7%

Keywords: LIDAR, DSM, DTM, Building Detection

1. Introduction

Light Detection and Ranging (LIDAR) data are derived from airborne laser scanning (ALS) with Inertial Measurement Unit (IMU) and Global Positioning System (GPS). The data are regarded as Digital Surface Model (DSM). There are a number of techniques for Digital Terrain Model (DTM) generation from LIDAR data such as linear prediction, morphological filtering, static filtering spline approximations, shift invariant filters, and active shade model [1] [2] [3]. Some researches are further to perform object classification using LIDAR data [1] [4]. In this paper we assume the points of object above ground are higher than their surrounding and then perform two morphologic operations to segment objects from ground. Therefore the non-object points can be used to generate DTM. On the other hand, we also analyze the object-based statistics of slope difference for each object for building detection.

2. Object Segmentation and DTM Generation

In our research we assume that object points are locally higher than ground points in DSM data. Two mathematic morphologies – flattening operation and H-Dome transformation are used to perform object segmentation.

2.1 Flattening Operation

Flattening operation is a morphologic operation on grayscale image by using a flat structuring element. This operation is illustrated in figure 1 [5]. The O(f, g) is the flattening result by using flat structuring element g to perform opening on the original profile f. We use this operation to eliminate peak noise in DSM.

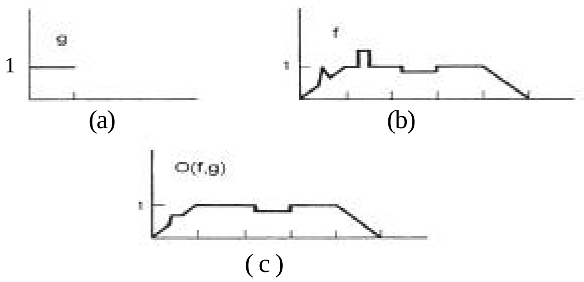

Fig 1. Flattening operation: (a)Structuring element; (b)Original profile; (c)Flattened result

2.2 H-Dome Transformation

The H-Dome transformation is developed to detect objects as local maxima [6]. This operation is illustrated in figure 2. An operator surface is lower than the original. Every point in the operation has to be pulled up to the same height of its neighbor and must be limited to the original height. This

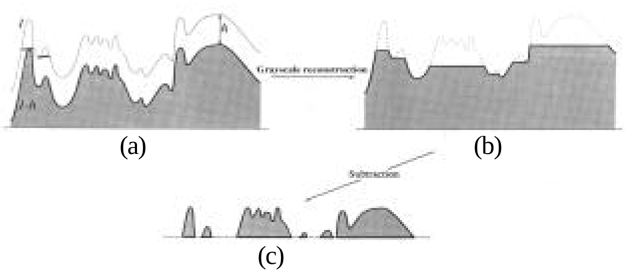

Fig. 2. H-Dome transformation: (a) Original profile; (b) Segmented background; (c) Segmented object

operation can perform surface reconstruction to segment objects above ground.

2.3 Searching for Control Posts and Surface Reconstruction

The parameter g, the size of the flat structuring element, can be reasonably set to 3m*3m for peak noise filtering. But the parameter h, the down height for operator surface, depends on object height and terrain type. The value is difficult to determine automatically. Therefore at the beginning we use two morphology methods with default parameters to perform initial object segmentation. Then ground points around these initial objects are called control posts. The new parameter h is defined by the maximum height difference between the objects and their nearest control posts. Then we add height h to all control posts. The two morphology operations are repeated to perform surface reconstruction for object segmentation.

3. Building Detection

The objects above ground include buildings, vegetation, cars and so on. We assume some properties of building to sift candidates from all objects and then analyze the object-based statistics for building detection.

3.1 Pre-processing for Building Candidates

We select criteria for sifting candidates: a building must be higher than 3m, wider than 10m, and bigger than $60m^2$. We slice object heights with 3m and perform opening operation in the object image. The objects with area smaller than 60 m^2 are eliminated.

We assume that the roof of building is flat or homogeneous inclined to be plane or slope. Therefore we compute slope difference for candidate points in objects. The slope difference is calculated by equation (1).

H1	H2	H3
H8	H0	H4
H7	H6	H5

S1=abs(H1-H0)-abs(H5-H0)

S2=abs(H2-H0)-abs(H6-H0)

S3=abs(H3-H0)-abs(H7-H0)

S4=abs(H4-H0)-abs(H8-H0)

dS=min(abs(Si)) (1)

3.2 Object-based Statistics

We normalize the slope difference to grayscale and compute each probability of gray level based on objects. Then eight object-based statistics are computed by equation (2)~(9), where Pi means the probability of gray value i.

1. area: number of grayvalue 0 (2)
2. contrast: $\sum_i \sum_j (i-j)^2 \times \min(P_i, P_j)$ (3)
3. entropy: $-\sum_i P_i \times \log P_i$ (4)
4. mean: $m = \sum i \times P_i$ (5)
5. maximum probability: $\mathrm{Max}(P_i)$ (6)
6. homogeneity: $\sum_i \sum_j \frac{\min(P_i, P_j)}{1+(i-j)^2}$ (7)
7. shape factor: $\sqrt{area} / perimeter$ (8)
8. variance: $\sum (i-m)^2 \times P_i$ (9)

3.3 Object-based Building Detection

We used two Neural Network models, Self Organization Map (SOM) and Back Propagation (BP), to classify candidate objects for building detection. SOM is an unsupervised classification method, which is used first to check the suitability of classifying candidates into two classes: building and non-building. BP is a supervised classification method. The eight statistics are all set to input layers for those two kinds of classification.

4 Experimental results

The test data is scanned by ALS40 system with a density of about 4 points/m^2 around Hsin-Chu Scientific Area in Taiwan. The position accuracy is about 30cm and the height accuracy is about 12cm. The data has been separated into surface points and ground points. The original data are regarded as DSM and the ground points are regarded as true DTM for accuracy assessment. These discrete points in an area of 850m*1060m are interpolated into 1m spacing grid by Kriging method. Figure 3 shows the DSM image generated with ground points.

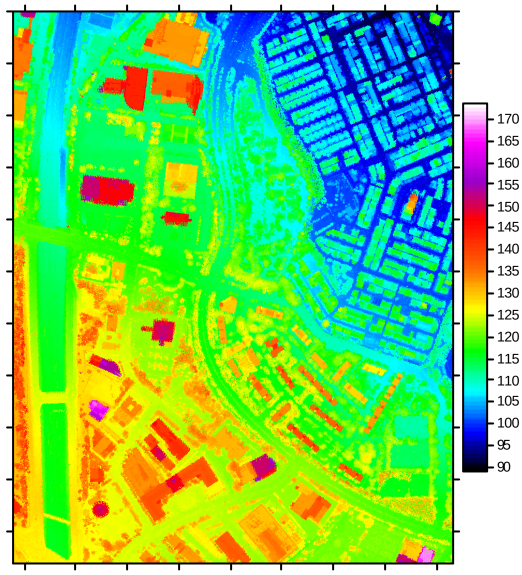

Fig. 3. DSM image from LIDAR data

4.1 DTM Generation

Figure 4 shows the object points in black and non-object points in white. The non-object points are regarded as ground points, which are interpolated to generate a DTM. Figure 5 shows the result of DTM generation. By checking the DTM at those ground points in the raw data set, we have -0.16m and 0.45m for mean error and RMSE, respectively.

Fig. 4. The object points (black) and ground points (white)

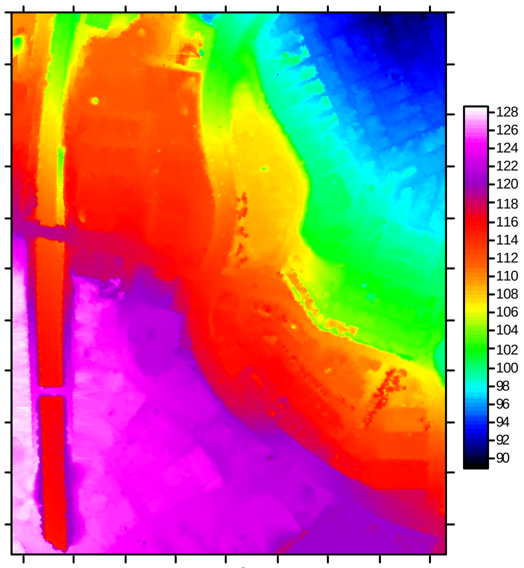

Fig. 5. The result of DTM generation

4.2 Building Detection

Figure 6 shows the result of building detection. There are 201 buildings in the test area. The proposed scheme misses 8 buildings. That indicates the object segmentation by two morphology methods is not quite perfect. When we perform the maximum probability of object-based statistics of slope difference, 183 buildings and 123 non-buildings are detected successfully. Among those erroneous detections 10 buildings are miscounted as non-buildings and 26 non-buildings on the contrary. Some errors are caused by the mixed pixels of building and vegetation. The total successful rate is 87.7%.

Fig. 6. The result of building detection

5. Conclusion Remarks

The experimental results are promising with the mean error -0.16m and RMSE 0.45m in DTM generation for a complex terrain. The successful rate is 87.7% for building detection. The DTM errors occur on ramps covered with buildings and vegetation. The building detection errors are caused by the segment objects mixing building and vegetation.

References

[1] Lohmann, P., 2002. IAPRS, Vol.34, Part2, Commision II, Xi' an, Aug., 311-315.

[2] Masaharu, H. and Ohtsubo, K., 2002, A Filtering Method of Airborne Laser Scanner Data for Complex Terrain. ISPRS Commision III, Working Group III/3, Sysposium 2002, september 9-13, Graz, Austria.

[3] Elmqvist, M., 2001. Ground Estimation of Laser Radar Data Using Active Shape Models. OEEPE Workshop on Airborne Laserscanning and Interferometric SAR for Digital Elevation Models. Stockholm.

[4] Schieve, J., 2001, "Region-based Information Extraction form Laser Scanning and Optical imagery", OEEPE Workshop on Airborne Laserscanning and Interferometric SAR for Digital Elevation Models, Stockholm, 2001.

[5] Dougherty, Edward R. 1992. An Introduction to Morphological Image Processing, SPIE Optical Engineering Press, Center for Imaging Science Rochester Institute of Technology.

[6] Vincent, L. 1993. Morphological Grayscale Reconstruction in Image Analysis: Applications

and Efficient Algorithms, IEEE, Trans. on Image Processing, Vol.2, No.2, 176-201