OBJECT-BASED BUILDING DETECTION FROM LIDAR DATA AND HIGH RESOLUTION SATELLITE IMAGERY

Tee-Ann Teo, Liang-Chien Chen
Center for Space and Remote Sensing Research,
National Central University, Chung-Li, Tao-Yuan 320, Taiwan.
Tel: 886-3-4227151-57623 Fax: 886-3-4254908
Email: {ann, lcchen}@csrsr.ncu.edu.tw

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ABSTRACT:
This paper presents a scheme for building detection from LIDAR data and high resolution satellite imagery. The proposed scheme comprises two major parts: (1) segmentation, and (2) classification. Spatial registration of LIDAR data and high resolution satellite images are performed as data pre-processing. It is done in such a way that two data sets are unified in the object coordinate system. Then, a region-based segmentation and object-based classification are integrated for building detection. In the segmentation, the LIDAR points are resampled to raster form. We, then, combine the elevation attribute from LIDAR data and radiometric attribute from orthoimages in the segmentation. The data with similar heights and spectral attributes are merged into a region. In the classification, we use the object-based classification to separate the building and non-building regions. The attributes considered in the classification include: (1) the elevation information from LIDAR data, (2) the spectral information from multispectral images, (3) the texture information from high spatial resolution image, (4) the roughness of LIDAR surface, and (5) the shape of regions. LIDAR data acquired by Leica ALS 40 and QuickBird satellite images were used in the validation.

1. INTRODUCTION

Extraction of the land cover information from remote-sensed data is an important work in the geographic information systems. The building region is one of the important land types in land cover classification. The extracted building regions are useful for disaster monitoring, decision making and in building reconstruction (Nakagawa, *et. al.*, 2002; Rottensteiner and Jansa, 2002; Vosselman, 2002), as well as other applications. Traditionally, building regions are extracted from image data. As the image data is lack of height information, it can only extract the 2D building region, rather than the 3D building object. In order to solve this problem, fusion of different sensors in building detection is needed (Hoffmann and Van, 2001; Schiewe, 2003).

Nowadays, LIDAR (LIght Detection And Ranging) has become a well-established technique for deriving 3D information in mapping and GIS tasks. LIDAR data provide highly accurate 3D points but lack breakline information. On the contrary, high resolution satellite imagery provides more accurate breaklines information than LIDAR data. Moreover, multispectral imagery is beneficial to identify and classify objects, such as building and vegetation. Thus, we propose to combine LIDAR data and high resolution satellite images for the building detection. A number of investigations have been reported regarding the land-use classification from LIDAR and other data source (Halla and Walter, 1999; Zeng, *et. al.*,2002; Walter, 2004; Hofmann, *et. al.*, 2002). Those investigations show that the additional height information is beneficial to object classification.

In this study, we focus on building region extraction using the object-based classification. The proposed scheme comprises two major parts: (1) segmentation, and (2) classification. Spatial registration of LIDAR data and high resolution satellite images are performed as data pre-processing. It is done in such a way that two data sets are unified in the object coordinate system. Then, a region-based segmentation and object-based classification are integrated for building detection. In the segmentation, the LIDAR points are resampled to raster form. We, then, combine the elevation attribute from LIDAR data and radiometric attribute from the image in the segmentation. The data with similar heights and spectral attributes are merged into a region. In the classification, we use the object-based classification to separate the building and non-building region. The attributes considered in the classification include: (1) the elevation information from LIDAR data, (2) the spectral information from multispectral images, (3) the texture information from high spatial resolution image, (4) the roughness of LIDAR surface, and (5) the shape of regions.

2. PREPROCESSING

The data preprocessing consists of two steps, which are interpolation of LIDAR data and space registration.

2.1 Interpolation LIDAR Data

The LIDAR data includes three dimensional coordinates of ground points and surface points. Those two sets of data may be used to generate DTM and DSM in grid form (Briese et al, 2002). Considering that the triangulated irregular network (TIN) approach provides the best results (Behan, 2000), we select TIN-based interpolation method is applied to rasterize the LIDAR data. In the rasterization, a median filter is applied to reduce the noise.

2.2 Space Registration

The objective of space registration is to establish the spatial relationship between the LIDAR data and the satellite images. We use ground control points to reconstruct the mathematic model for space registration. Hence, the LIDAR data and the satellite image are co-registered in the same georeference system. In the registration, rational function model approach is applied for simplicity (Fraser and Hanley, 2003).

3. BUILDING DETECTION

The objective of building detection is to extract the building regions. There are two steps in our scheme: (1) region-based segmentation, and (2) object-based classification. The flow chart of building detection is shown in Figure 1.

3.1 Region-based Segmentation

There are two ways to do the segmentation. The first one is the contour-based segmentation. It performs the segmentation by using edge information. The second one is the region-based segmentation. It uses a region growing technique to merge pixels with similar attribute (Lohmann, 2002). We select the region-based segmentation because its noise tolerance is better than contour-based segmentation. We combine elevation attribute from LIDAR data and radiometric attribute from orthoimages in the segmentation. The pixels with similar height and spectral attribute are merged into a region.

3.2 Object-based classification

After segmentation, an object-based classification rather than pixel-based classification is performed. Each separated region after segmentation is a candidate object for classification. An object-based classification considering the characteristics of elevation, spectral, texture, roughness, and shape information is performed to detect the building regions (Hofmann, et. al, 2001). The LIDAR data and the satellite image are integrated in this stage. The characteristics are described as follow.

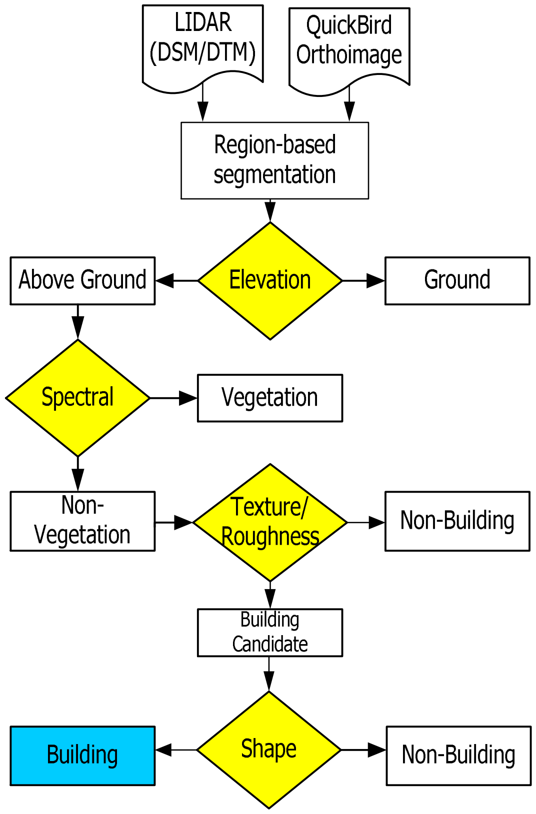

Figure 1. Flow chart of building detection.

Elevation: Subtracting DTM from DSM, we generate the normalized DSM (nDSM). The data describes the height information above ground. Setting an elevation threshold one can separate the object above ground from the ground. The above ground surface includes building and vegetation that are higher than the elevation threshold.

Spectral: The spectral information comes from QuickBird multispectral images, which includes blue, green, red, and near infrared bands. The near infrared band gives the useful spectral information for vegetation. A well-known Normalized Vegetation Index (NDVI) is used to distinguish vegetation from non-vegetation areas.

Texture: Several papers demonstrated that texture information is useful for building detection (Zhang, 1999). Panchromatic images preserve more texture information due to its higher spatial resolution. We use the Grey Level Co-occurrence Matrix (GLCM) for texture analysis. GLCM is a matrix of relative frequencies for pixel values occur in neighboring processing windows. We select the **entropy** and **homogeneity** to compute the co-occurrence probability. The role of texture information is to separate the building and vegetation when the objects have similar spectral response.

Roughness: The roughness of LIDAR data aims to classify the vegetation regions and non-vegetation ones. The surface roughness is similar to the texture information of spectral data **(**Mass, 1999**).** The role of surface roughness is to separate the building and vegetation when the objects have similar spectral response. We use the variance of slope as the roughness criterion.

Shape: The shape attribute includes size and length-to-width ratio. An area threshold is used to filter out those small objects. That means the regions smaller than a minimum area (e.g., $16m^2$) are discarded. The length-to-width ratio is suitable to remove the thin objects. The objects are eliminated when the length-to-width ratio is large than a threshold.

4. EXPERIMENTAL RESULTS

The LIDAR data used in this research covers an area in Hsin-Chu Science-based Industrial Park of north Taiwan. The data was obtained by Leica ALS 40 system. The discrete LIDAR points were classified into ground points and surface points. The average density of LIDAR data is about 1.6 pts/m^2. The ground resolutions of QuickBird panchromatic and multispectral satellite image are 0.7m and 2.8m, respectively.

The surface points and ground points from LIDAR data are rasterized to DSM and DTM both with a pixel size of 0.5m. The DSM and DTM are shown in Figure 2 and Figure 3. The QuickBird panchromatic image and multispectral image are rectified into orthoimage by using the LIDAR DSM. The orthoimages are shown in Figure 4 and Figure 5, respectively. The raster-based segmentation result is shown in Figure 6.

The classification result is shown in Figure 7. A 1/1000 scale topographic map was used to evaluate the classification results. The 1/1000 topographic map is shown in Figure 8. As we compared the classification results and topographic map, most of the building regions were accurately extracted. The undetected buildings are small ones. That is because small buildings are often with low elevation and have less texture information. Thus, the building blocks are influenced by neighbouring objects. Considering different land covers, the classification accuracy is 92%. On the other hand, if we only considered buildings, the detection rate is 89%. The accuracy performance is demonstrated in Table 1.

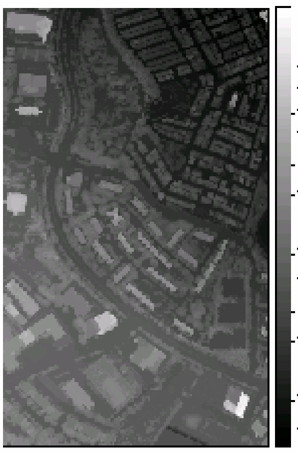

Figure 2. DSM

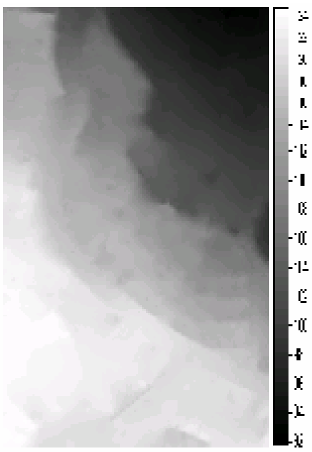

Figure 3. DTM

Figure 4. QuickBird panchromatic image

Figure 5. QuickBird multispectral image

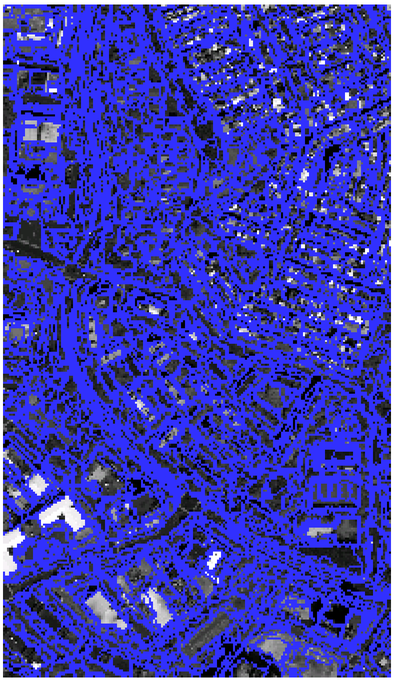

Figure 6. Result of segmentation

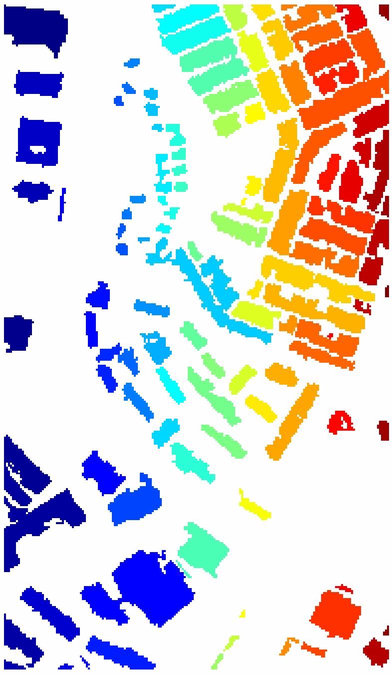

Figure 7. Result of building detection

Figure 8. Building regions from 2D topographic map

Table 1. Accuracy assessment for building detection

		Classified Data		
	Unit: pixel	Building	Non Building	Total
Reference Data	Building	a=653218	b=74227	e=727445
	Non Building	c=97246	d=1585730	f=1682976
	Total	g=750464	h=1659957	i=2410421
		Diagonal Total		2238948
	Producer	a/e=89%	d/f=94%	91.5%
	User	a/g=87%	d/h=95%	91%
	Overall (a+d)/i	-	-	92%

5. CONCLUSIONS

In this investigation, we have presented a scheme for the extraction of building regions by performing fusion of LIDAR data and high resolution satellite imagery. The results from the test have shown the potential of the automatic method for building detection. More than 89% building regions are correctly detected by our approach. Most of the undetected building regions are the small buildings. Those errors are majorly introduced in the segmentation stage. Further investigation of small buildings detection is needed.

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