OBJECT-BASED LAND COVER CLASSIFICATION OF URBAN AREAS USING VHR IMAGERY AND PHOTOGRAMMETRICALLY-DERIVED DSM

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ABSTRACT

Object-based image analysis is becoming increasingly popular in classification of very high resolution (VHR) imagery over urban areas. The spectral resolution of VHR imagery (generally they possesses 1 pan and 4 multispectral bands), however, is limited and insufficient for differentiating many urban land cover classes. Due to the spectral similarity of building roofs, roads and parking lots, spectral-based classifications which solely rely on spectral information of the image do not have promising results when applied to VHR imagery over urban landscapes. In recent years, significant amount of research has been carried out on incorporating LiDAR derived DSM into the classification to address the problems of differentiating spectrally similar objects in urban areas. However, LiDAR DSMs are expensive and not available for many urban areas. In this research, we introduce a new approach for classifying urban land cover classes by incorporating widely available photogrammetrically-derived DSMs. Even though the accuracy of photogrammetrically-derived DSMs is far below that of LiDAR DSMs, and significant misregistration exists between VHR imagery and DSM, object- based hierarchical fuzzy classification still achieve successful separation between building roofs and traffic areas. Stereo aerial photos and a pansharped QuickBird multispectral image of the downtown area of the city of Fredericton, Canada, were used for this research. Results show that buildings can be well separated from roads and parking lots, and the proposed approach has the potential to replace LiDAR DSM for urban land cover classification.

KEYWORDS: Feature Object-based classification, segmentation, DSM, misregistration

INTRODUCTION

Mapping urban areas using VHR imagery has attracted significant amount of research in recent years, particularly with the availability of satellite VHR imagery such as IKONOS, QuickBird, GeoEye-1, WorldView-1 and WorldView-2. This is because of the broad coverage, fast acquisition, and relative inexpensive price of such imagery. Conventional spectral-based classification approaches that have been successfully applied to low resolution satellite imagery do not have promising results when applied to VHR imagery in order for mapping urban environments. The spectral diversity within the same land cover and spectral similarity among different land cover along with the spectral limitation of VHR imagery make the classification of such imagery very challenging task. To overcome this problem, in recent years, many researchers have tried to employ spatial information in addition to spectral information of VHR imagery in classification procedure. The spatial information can be derived from the image in the forms of texture, morphology, and context or it can be extracted from other ancillary data such as digital surface models (DSM) and existing GIS layers. Heinl et al. (2009) showed that the use of ancillary data improves the classification accuracy independent of classification method. In fact, ancillary data layers are a key component to accurate image classification (Thomas et al., 2003).The importance of integration of ancillary data with VHR imagery, in order for detailed mapping of urban environments, becomes more significant particularly with the wide availability of VHR imagery, DSM extracted from LiDAR data (LiDAR-derived DSM) or optical stereo images (photogrammetrically-derived DSM), and existing GIS data layers.

In terms of utilizing LiDAR data in classification, particularly object-based approaches, a considerable amount of literature has been published in recent years and results shows significant improvement in classification accuracy of impervious surface such as buildings, roads, and parking areas. Exemples are Syed et al. (2005a), Syed et al. (2005b), Haitao et al. (2007), Sohn and Dowman (2007), Kressler and Steinnocher (2008), and Watanachaturaporn et al. (2008). LiDAR data, however, is expensive and not easily available for many places. On the contrary, photogrammetrically-derived DSM is either available in archive for many areas or it is achievable (with the recent availability of VHR stereo aerial/ satellite imagery). Nevertheless very few studies have benefited from this type of DSM in classification of urban areas (e.g. Hussain and Shan, 2010). A key problem in integrating of ancillary data, especially photogrammetrically-derived DSM, with VHR imagery is the misregistration between two data sets. This problem is more severe if pixel-based approaches are employed for classification. Indeed, with the sub-meter resolution of VHR imagery, it is hard to achieve a pixel by pixel registration between heights and the image. In object-based approaches, however, the mapping unit is a connected group of pixels and it is not required to have a pixel by pixel registration between corresponding data layers. In fact, object-based approaches facilitate the use of ancillary data (Kim et al., 2010).

This paper aims to explore the potential of DSM generated by stereo optical images in classification of VHR imagery over urban areas. Particularly, the attention is to classify large buildings in an urban landscape using hierarchical rule-based fuzzy classifier of object-based classification, VHR imagery and photogrammetrically-derived DSM.

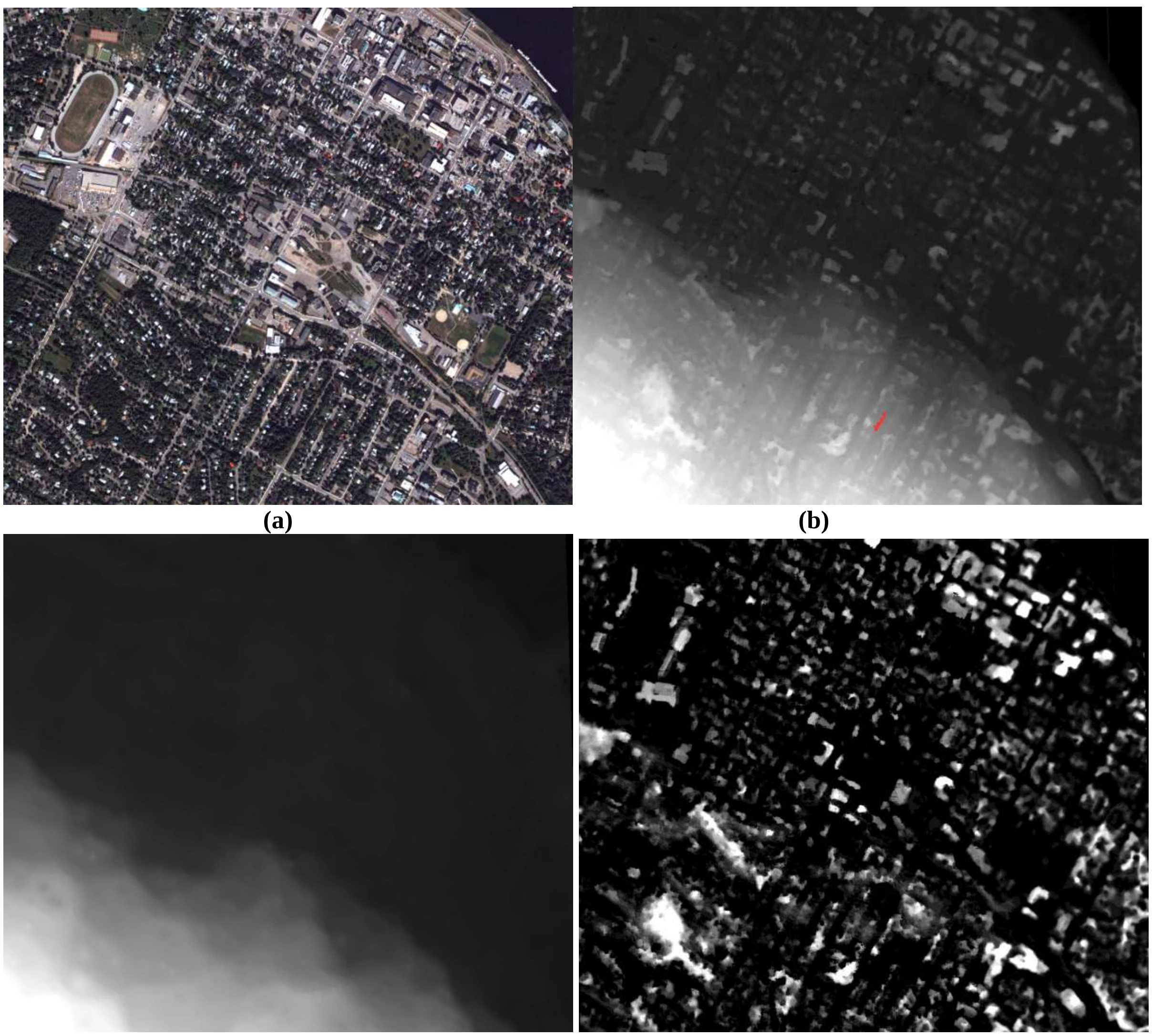
STUDY AREA AND IMAGE DATA

The study area is a part of city of Fredericton, Canada. This area contains large residential and commercial buildings as well as small family houses, streets, vegetation, and parking areas. Two datasets were used in this research including a part of a Quickbird scene acquired in late summer of 2002 and two pairs of aerial photos from the same area taken in summer 2005. As a pre-processing step, four multispectral bands of Quickbird were fused with the panchromatic band using UNBPansharp algorithm (Zhang 2004) to generate four pansharped bands with the spatial resolution of panchromatic band. The aerial photos, used in this study, have the scale of 1:10000 and were scanned with 50 microns of resolution generating a pair of 0.5 m ground pixel size images. The scanned aerial photos were used for generating digital surface model (DSM) of the area. Figure 1 depicts the first stereo pair of aerial photos used in this work.

Figure1. The first pair of stereo aerial photos of the study area.

DSM GENERATION USING STERO AERIAL PHOTOS

As mentioned earlier, two overlapping pairs of scanned aerial photos (four photos) were employed to generate the digital surface model of the study area. PCI Geomatica OrthoEngine 10.3 was used for DSM generation. Each photo was first internally oriented by camera calibration information to adjust the photo coordinate system. No GCP were used in the exterior orientation procedure. Instead, the exterior orientation parameters, including three shifts and three orientation angles for each stereo pair, provided by the onboard GPS-INS equipment, were directly utilized in order for generating the epipolar plans for left and right photos. Figure 2 (b) shows the generated DSM. The DSM represents the height of each pixel from the reference datum, which is not a good representation of high rise features (i.e. built-up features and trees). In fact, what it is needed here is the relative height of objects from the ground not from the datum. Therefore, we need to remove the underlying terrain to produce the height of objects above the local ground (Barnsley et al., 2003; Ma, 2005). The resultant height is referred to the normalized DSM (nDSM) (Chen et al., 2009). In this research, the local ground height, also known as digital terrain model (DTM), were subtracted from DSM to generate the nDSM. Figure 2 depicts the pansharped Quickbird image, the generated DSM, the DTM and the resultant nDSM for the study area. The nDSM was later used to distinguish between buildings from streets and sparking areas in classification procedure.



(a) **(b)** **(c)** **(d)**

Figure 2. Quickbird image (a), generated DSM from stereo pairs photo (b), digital terrain model (c), and nDSM(d) of the study area.

SEGMENTATTION

The first step in object-based classification is segmentation, which is the process of partitioning the image into a set of discrete, non-overlapping regions on the basis of internal homogeneity criteria (Devereux et al., 2004). Furthermore, land cover of different types, particularly buildings and vegetation areas which are of interest in this research, presents in various shapes and sizes in the image, and cannot be well extracted by single resolution segmentation. To overcome the undersegmentation and oversegmentation problems, the multi-resolution segmentation, embedded in eCognition Developer software, was employed in this research. Smaller land cover types such as single trees are well segmented in the lower levels of segmentation, while objects in higher levels of segmentation are more meaningful for larger land cover types. Three parameters including scale, shape and compactness should be defined for each level of segmentation in multi resolution segmentation. The selection of optimal parameters is a trial and error process, which depends on the analyst's experience.

A semi-automatic process of selection of optimal parameters, which is called Fuzzy-based Segmentation Parameter optimizer (FbSP optimizer), developed at the University of New Brunswick (Zhang and Maxwell, 2006, Zhang et al., 2010) was used in this work. To use the FbSP optimizer, an initial segmentation is performed by manually selecting the parameters (level 1). Normally the color and compactness are left as eCognition default and the scale parameter is set in such a way that the resultant objects are smaller than the real objects (small scale). These small objects, also called sub objects (Zhang et al., 2010), and their corresponding target objects are then used to train the FbSP optimizer. After the training, the FbSP optimizer gives the optimal parameters for the second level of segmentation. Table 1 reports the segmentation parameters in each level. Objects in the first and second levels of segmentation, in this study, were optimal for class of vegetation and buildings, respectively.

Table 1. Multi-resolution segmentation parameters

Level	Scale	Color	Compactness	No of Objects
1	30.00	1.00	0.50	67405
2	78.74	0.60	0.80	8538

CLASSIFICATION AND RESULTS

The fuzzy logic nearest neighbour and the hierarchical rule-based fuzzy classifiers are two well known object-based classifications. The nearest neighbour is a supervised classification based on chosen sample objects, while hierarchical classification is a rule-based approach that works based on each class description. In this research, hierarchical fuzzy rule based classification was employed in order to classify the area. Since the objective is to classify buildings by integrating the DSM and VHR imagery, other impervious classes such as small houses, roads, and parking areas were not considered in classification procedure.

To do this, a hierarchical rule set was developed. The rule set starts to classify the entire area into vegetation and non-vegetation using the normalized different vegetation index (NDVI) calculated from four pansharped bands of the Quickbird image. Because of the presence of small grass areas and single trees, first level of segmentation, in which small objects are better represented, was utilized in the classification of the image to vegetation and non vegetation. Non vegetation areas were further classified to shadow and non shadow. The reason why shadow was considered in the classification procedure is that tall buildings cast shadow and if it is not extracted first, it will later affect the classification of buildings. Shadow is a dark feature in the pansharped Quickbird image and is relatively easy to be extracted using the mean brightness values of all bands. Finally, non shadow areas were divided to buildings and other impervious classes.

Buildings are relatively well represented by objects in level two of segmentation. However, classifying buildings' object is not promising exclusively based on the information extracted from the image. This is because of the spectral and spatial similarity among buildings, houses, roads, and parking areas. On the other hand, buildings are distinguishable from other impervious surface classes by their heights, offered by the nDSM. However, when the nDSM, generated from aerial photos, is integrated with the Quickbird image misregistration between two data sets is a problematic issue. The misregistration between nDSM and the image is illustrated in figure 3. Fortunately, this misregistration effect is mitigated when objects, instead of pixels, are utilized. Figure 3 also shows the classification result of the small part of the image. As can be seen in this figure, despite the significant shift between the buildings's roof (indicated by red boundary) and the corresponding nDSM height, the classifier has classified this building correctly.

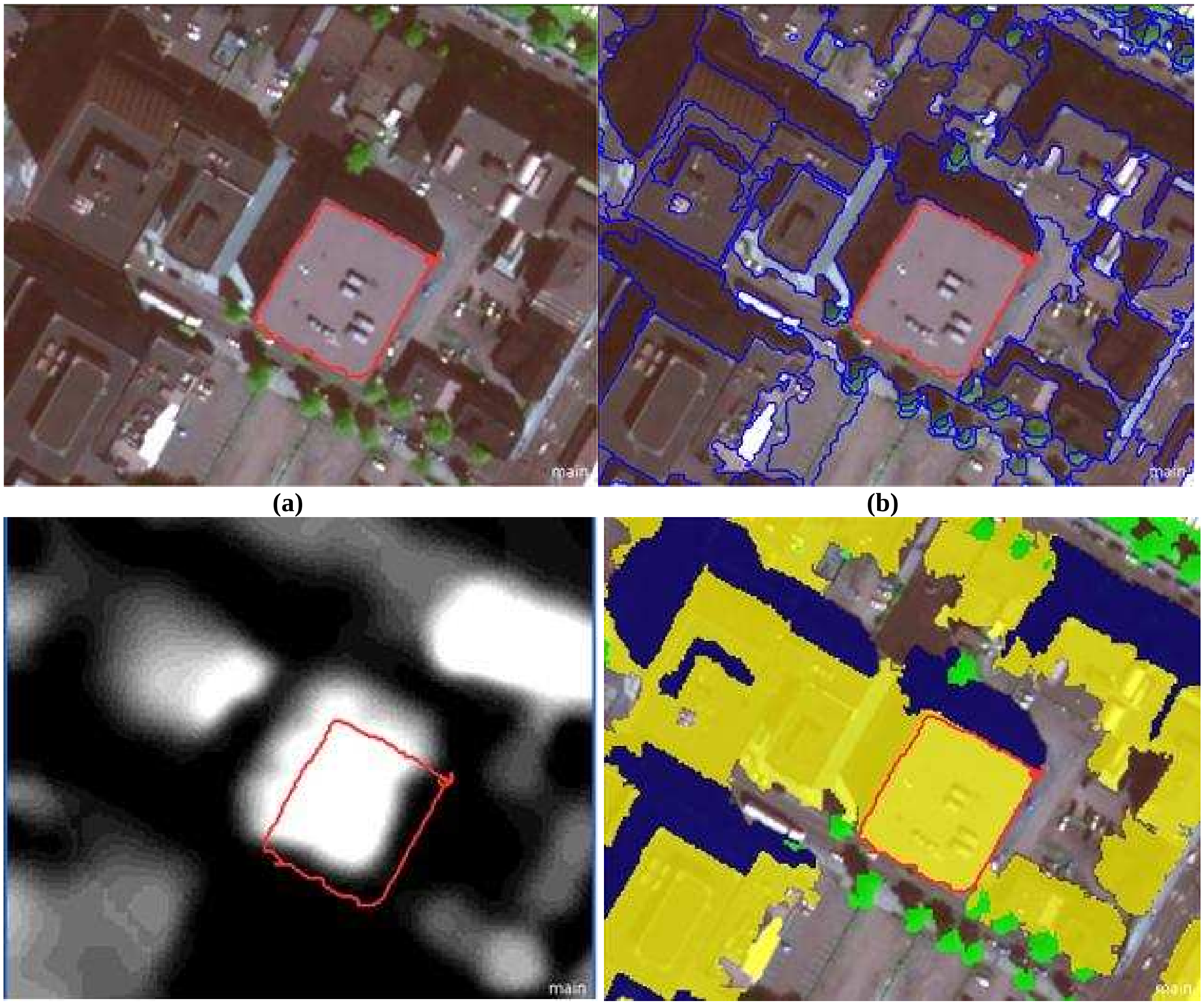


Figure 3. The pansharped image (a), segmentation image (b), the nDSM (c), and classification into three classes (d) (yellow: buildings, blue: shadows and green: vegetation).The misregistration between the segmented image and nDSM is shown in the nDSM image.

The classification result of the entire area is represented in figure 4 where buildings, vegetation and shadows are represented in yellow, green, and blue, respectively. Since the class of water was not of interest in this study, it was not defined in the rule sets. Consequently a part of the river in top-right corner of the image is classified as shadow. The classification result of vegetation and shadow areas are near to perfect when the original image (figure 2(a)) is compared to classification result (figure 4). The salt and pepper effect of pixel-based classification approaches are completely removed, since the classification is performed on objects (which are homogeneous) rather than on pixels. In fact segmentation stage decreases variance within the same land cover type by averaging the pixels within the object, which prevents the salt and pepper effect. Visual inspection of the classification results confirms that buildings are relatively well extracted in the area. This can be seen in the downtown area of the city (top-right), where almost all buildings are extracted properly. Also buildings located in the centre, bottom-left and building near the stadium are all extracted by the classifier.

Figure 4. Classification results of three classes (vegetation: green, buildings: yellow, and shadow: blue) overlaid on top of the original image.

CONCLUSION

Adding ancillary data to spectral bands of VHR imagery over urban areas is critical for classifying spectrally similar classes such as buildings and traffic areas. Particularly, the height information from photogrammetrically-derived DSM is very practical, due to the wide availability of stereo aerial/satellite images, and helpful in separating built-up from traffic areas (i.e. roads and parking lots). Although precise pixel by pixel geometric registration between the DSM and VHR imagery is hard to achieve, object- based classification facilitates it by segmenting the image and finding the corresponding segment in the DSM. Furthermore, multi resolution segmentation provides segments with different sizes and shapes in different levels, which accordingly land covers with various sizes are well represented (e.g. single trees are represented in lower levels and large buildings in higher levels of segmentation).Since the class of vegetation and shadow influence the classification of buildings using nDSM, these two classes should first be classified. Classification of these two classes is relative easy exclusively using the spectral bands of VHR imagery. The result of this work shows a near to perfect classification of vegetation and shadow. Shadow later can be reclassified to some land cover types by contextual information of surrounding classes. Visual inspection of the classification result reveals the high potential of photogrammetrically-derived DSM in conjunction with VHR imagery and object-based image analysis in extraction large buildings in a typical urban environment.

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