BUILDING DETECTION IN VERY HIGH RESOLUTION SATELLITE IMAGE USING IHS MODEL

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ABSTRACT

Detection of buildings in urban and suburban areas using very high resolution satellite (VHR) images is a challenging task due to different illuminations on different sides of the same building roof. This causes different brightness values on a single roof. Therefore, in the segmentation step of an object-based classification, different sides of a roof will be assigned to different segments due to their intensity variation. To solve this problem, the majority of the studies merge the building roof segments together based on elevation information. However, because of the uncertainty of the borders in elevation layers as well as misregistration between the spectral and elevation layers, building boundaries usually cannot be detected precisely. In this study a novel method which utilizes IHS color transform is used to overcome the problem of intensity variation to segment each building roof as one segment. Then, the elevation information from LiDAR data is used to differentiate roof segments from other segments.

The proposed method is tested on the QuickBird satellite imagery of Fredericton, Canada. The achieved results are quite promising with an overall accuracy of more than 90% for building detection. Considering the off-nadir situation of imagery and consequently miss-registration between the elevation data and the image, the produced unified color segments are of great benefit for precise building boundary detection.

Key words: Building Detection, IHS, Segmentation, Object Based Classification

INTRODUCTION

The main purpose of this study is to find buildings in VHR imagery. However, due to the complexity of the mentioned task, some ancillary data is required (Bouziani M.,Goïta K., He D.C., 2010; Moskal, Styers, & Halabisky, 2011; Thomas, Hendrix, & Congalton, 2003,; Watanachaturaporn, Arora, & Varshney, 2008). Here, elevation information is used as an ancillary data in an object based building detection methodology. This study assumes that buildings are typically rectangular shaped elevated features (Jabari & Zhang, 2013) with constant color on their roofs. Based on the aforementioned assumption, elevation, shape, and color information of the segments are used in order to detect buildings. The elevation information is generated using LiDAR data; the shape information is generated using geometric features in eCognition software; the color information is generated using IHS color system. Later on, using a fuzzy inference system, the candidate building segments are selected.

DATA AND METHODOLOGY

In this study, LiDAR data as well as QuickBird satellite images of Fredericton, NB, Canada are used. Figure 1(a) shows a part of the study area. In this study, after generating the elevation layers, vegetation is supressed from the study areas to limit the search area for building detection.

Elevation Layer Generation

LiDAR data is used for generating the DSM and DTM. Accordingly, the normalized digital surface model (nDSM) which shows the height above the ground is also generated.

$$nDSM = DSM\text{-}DTM \tag{1}$$

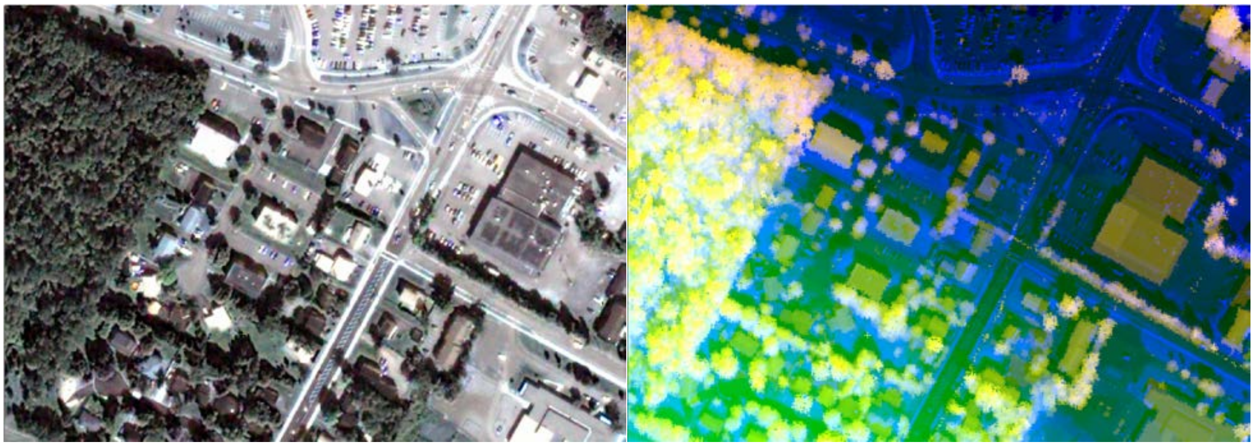

Figure 1: (a) A part of the study area, QuickBird image of Fredericton, NB, Canada; (b) Elevation layer (yellow color) on top of the spectral band (blue color)

The elevation information along with the spectral information is used to detect buildings. However, since the image coordinate system of satellite images is not consistent with DEM coordinate system, which is generally a ground coordinate system such as UTM, using image RPCs (Rational Polynomial Coefficients), elevation information is transferred to the image space (Jabari, Zhang, & Suliman, 2014); The DEM is called elevation layer. Equation 2 shows the RPC formulas for transformation of the normalized ground coordinates to the associated image coordinates (Grodecki, 2001).

$$\begin{aligned} x &= \frac{a_0 + a_1X + a_2Y + a_3Z + \cdots + a_{19}Z^3}{b_0 + b_1X + b_2Y + b_3Z + \cdots + b_{19}Z^3} \\ y &= \frac{c_0 + c_1X + c_2Y + c_3Z + \cdots + c_{19}Z^3}{d_0 + d_1X + dY + d_3Z + \cdots + d_{19}Z^3} \end{aligned} \tag{2}$$

where, x and y are normalized image coordinates; X,Y, and Z are normalized geodetic ground coordinates. And the coefficients a_i, b_i, c_i and d_i are given by the image vendor in RPC files. Once they are known, the transformation from object space into image space can be performed using ground coordinates (X, Y, Z) from DSM layer.

Nevertheless, due to the existence of a bias in the vendor provided RPCs (Fraser & Hanley, 2003), the transferred elevation information, does not line up with the associated image objects. (Fraser & Hanley, 2003) suggest using a conformal transformation to compensate the inherent bias (Fraser & Hanley, 2005) in RPCs to produce highly accurate DEMs; in this study, the same conformal transformation is inspired from (Fraser & Hanley, 2003)'s work to line up the image objects with their associated elevation information. Therefore, using 4 tie points, whose coordinates are known both in the elevation layer and the image layer, the 4 conformal transformation unknowns are solved. Later on, using the so produced coefficients, elevation layer coordinates are bias compensated. Figure 1(b) shows how properly the transferred elevation lines up with the image objects. The transferred DSM and nDSM layers are called height layer (H) and normalized height layer (nH), respectively.

Vegetation Suppression

After transferring the elevation layers to the image space, finding building places will be more straightforward using the height above the ground feature. However, as Figure 2 shows, building borders are not quite sharp in the elevation layers. Therefore, accurate building borders should be extracted using spectral information.

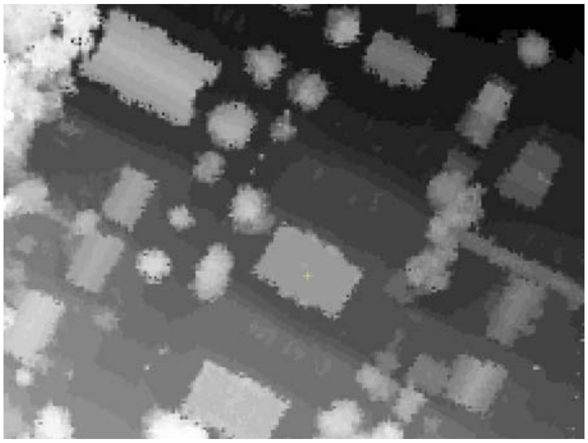

Figure 2: Height layer (H) with uncertain borders for image objects

Also, there are other high elevated features, which might be mistaken for buildings, within which the most important ones are trees. In this study, vegetation is removed from the search using two parameters: *NDVI* and *NIR ratio*. For more information about vegetation detection, refer to (Jabari & Zhang, 2013).

Building Detection

Detecting proper building borders requires the use of spectral information. However as stated in (Jabari & Zhang, 2014), buildings with pitched roofs, which are of the most common building roofs in areas with high amount of rainfall, produce difficulties in proper building border detection. As Figure 3 shows, the intensity of pitched roofs vary for different their different faces. Using IHS components instead of RGB color system, precise building borders can be detected (Jabari & Zhang, 2014).

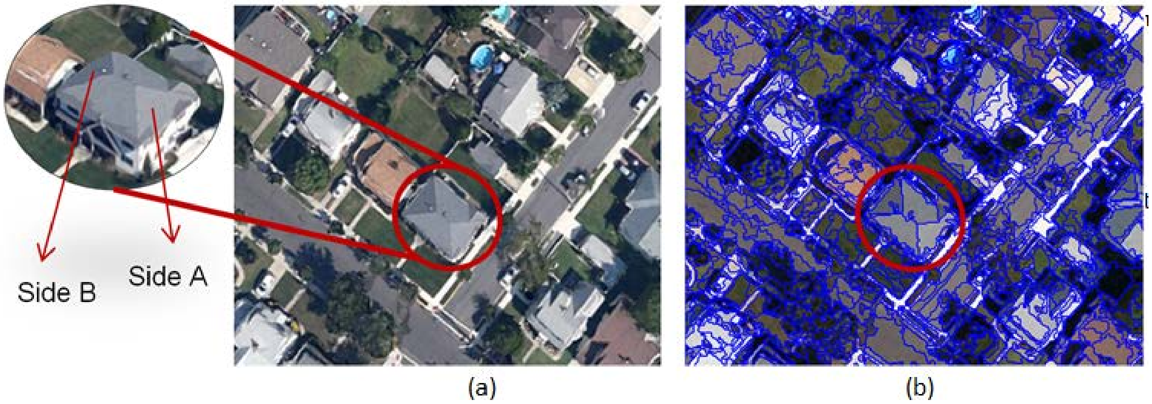

Figure 3: (a) A typical pitched roof building in a satellite image and its 3D model. (b) Segmentation result using a conventional approach; each side of the pitched roof is assigned to a different segment due to intensity variation.

After the proper segmentation to detect precise building borders using IHS color system, segments with the following specifications are selected as building candidates (Jabari & Zhang, 2013):

- elevation more than a specific threshold, in this study 2.5m,
- Area within a specific threshold (to remove non-building features such as trucks),
- high value of *rectangular fit*
- high value of *elliptical fit*

The last two features are selected from the eCognition software features, which indicate the degree of similarity of a segment to a rectangle or ellipse, respectively. The above features are used in a fuzzy inference system to decide whether a specific segment belongs to building class or not.

Later on, using some complementary rules such as removing elongated segments, which do not belong to the building class, buildings are outlined.

RESULTS AND CONCLUSION

Figure 4 shows the result of building detection in a part of the image. In order to check the accuracy of the work, buildings of a random part of the image are manually classified by an expert and the output is compared to the image classified by the presented methodology. The comparison illustrates that 100% of the buildings are detected using the methodology. However, in terms of border matching 93% of the buildings have borders more or less the same as the ones selected by human expert (with around 80% matching). 9% of the total numbers of the buildings were also false alarms, which belonged to road or vegetation class and were committed to the building class.

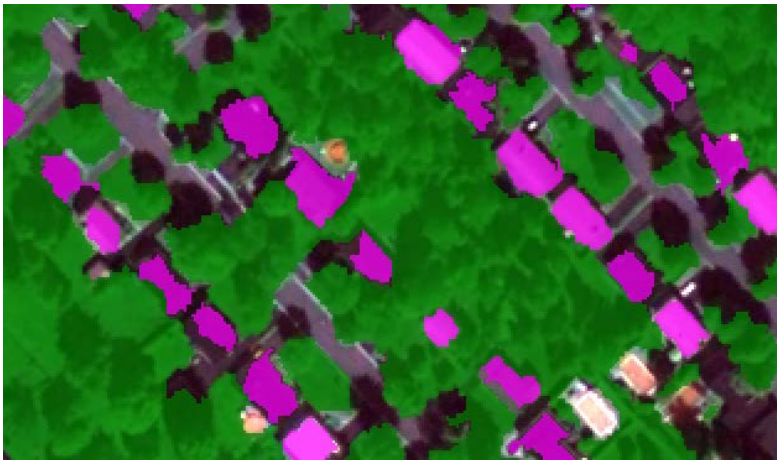

Figure 4: Building detection result

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