Object Based Image Analysis approach for extraction of Urban Tree Canopy

Abstract

Very high resolution (VHR) satellite imagery have brought out the new possibilities for remote sensing applications such as road, buildings and tree canopy extraction from complex area. Urban planners and government organizations need the detailed land cover information for sustainable urban growth and development model. The aim of this study is to extract urban tree canopy from Worldview-2 imagery using Object Based Image Analysis (OBIA) approach. OBIA is such a powerful paradigm where human interpretation is incorporated with the help of different rules and expert knowledge to enhance the extraction process of target object from imagery. OBIA operates on image object which acts as a source of information by providing characteristic facets. The proposed work is carried out in eCognition software environment with Cognition network language (CNL). Tree canopies having less contrast with background are detected by creating separate regions and vegetation obscured by shadow is also extracted using vegetation indices. These two challenging tasks in the extraction process of tree canopy are carried out by the proposed rule-set. Hierarchical level classification boosted the results of classification. Despite the spectral complexity of landscape in this study proposed rules achieve satisfactory output with overall accuracy of 88.12%.

Keywords: Segmentation, VHR satellite images, urban area, Vegetation, Hierarchical levels, OBIA

1. Introduction

Vegetation extraction is of great significance to urban planners and municipalities. It is the most important activity in understanding of urban ecosystems or to prepare development plans, to regulate and control the use of spaces in cities as well as to make sustainable development plans. Trees combat the climate change by absorbing carbon dioxide. It
provides Oxygen and cleans air. It not only provides the habitat for wildlife but also increases the property value by beautifying the landscape. Trees act like a sponge that filters atmospheric pollutants and keeps the city life clean and fresh. On hillsides or stream slopes, trees hold soil in place and avoid soil erosion. Tree lined streets have a traffic calming effect. Trees muffle urban noise almost as effectively as stone walls. Trees can be an asset to entire community with proper care and planning (Nowak et al. 1996). The traditional field survey methods are time consuming and not accurate. Updates are not frequent also manpower is required which increases cost.

Remote sensing has major contribution in urban planning and management as it gives detailed information of dynamic development of urban area. Satellite imagery could play an important role in mapping urban vegetation (Kumar and Roy. 2013). As frequent updates are possible along with that monitoring of specific vegetation species or change detection can be carried out.

Recent advances in the quality of satellite imagery and the desire to analyse this data has spurred the development of new image processing techniques for object extraction (Aguilar et al. 2013). Due to VHR satellite imageries scale of interest has been shifted from vegetation to individual tree.

To transfer the image data into meaningful information image analysis must be done in a proper way. OBIA is most convenient for interpretation of high resolution satellite images. It not only replicates the human interpretation but also provides more information than pixel based analysis (Blaschke et al. 2014). OBIA first segments the images into meaningful objects and then classifies them. In OBIA segmentation can be done with different algorithms and objects are formed iteratively. Li and Shao (2013) employed different segmentation algorithms to separate Woody plants, large lawn, small lawn, crop and grass. After primary segmentation further results are obtained by employing the human
expert knowledge to automate the process for land cover mapping (Benz et al. 2004). The classification accuracy and results can be improved by adding expert domain knowledge at different hierarchical level. Hierarchical level classification further enhances extraction process of specific target. Due to complex arrangement of city landscape it is difficult to address area of interest in image interpretation. A typical image comprised of features of various sizes. Large homogeneous objects within the scene can be extracted at large object size whereas the small heterogeneous objects can be classified at smaller object size. By classifying the image at multiple scales image objects are networked so that the each object can be related to its neighbor objects on given level, to its parents object at higher level as well as to its sub-objects in level below (Navulur 2006, Blaschke 2010). Vegetation in urban area is not precise; it is randomly present with varying area which further hinders the correct identification of tree.

Ample literature is present on Individual tree crown detection and delineation through various methods. Ke and Quackenbush (2011) and Yadav et al. (2015) have listed out different approaches. Valley-following, region growing are well known algorithms used widely and in addition wavelets are integrated to improve accuracy of classification (Theng and Ling. 2008). In the sparse riparian Tugai forest which is in an arid environment, region growing approach is used (Gartnera et al. 2014) to delineate tree crown areas and quantify crown diameter changes. Several other algorithms such as edge detection, template matching, contour based methods, watershed segmentation, 3D model-based methods have been developed for tree crown mapping. Edge detection followed by marker controlled watershed segmentation (Wang et al. 2004), detecting local extrema points in the Laplacian of-Gaussian scale-space which acts as tree centres and estimates crown sizes (Skurikhin et al. 2013) are a few other approaches developed earlier.
From multispectral imagery, the detailed vegetation classification of urban area is carried out with the aid of ancillary data sources which helps to distinguish between spectrally inseparable vegetation classes. Along with spectral properties slope, aspect, soil moisture and Hue-Intensity-Saturation (HIS) as additional data layers have shown to be important from classification point of view (Rapinel et al. 2014, Yu et al. 2006). Texture feature is also considered as a key point for classification specially for separating grassland and other vegetation classes (Zhang et al. 2001). GLCM (Gray level co-occurrence matrix) calculation demands high computation power which is the only limitation of texture feature. Texture features together with OBIA approach and artificial neural network (ANN) yielded significant increase in classification accuracy as compared to pixel based analysis (Pu et al. 2011). Contribution of lidar intensity and height information further improves the classification accuracy and can effectively separate the tall and mature trees from shrubs and bushes (O’Neil-Dunne et al. 2014, MacFaden et al. 2012).

In this study, the authors presented a rule based system for the extraction of tree canopy and classification of other vegetation area. The lower spectral separability of tree canopy with other vegetation area impedes the proper identification of tree crown. For such a challenging task spatial region approach is used and further, the vegetation area below shadow is extracted with the help of vegetation indices. The detailed rule based system for separation between classes of vegetation is discussed in next section.

2. Study Area

In this work, WorldView-2 (WV-2) imagery of Powai area of Mumbai City, acquired in November 2010 is considered. Very high spatial resolution of WV 2, combined with the increased spectral fidelity provides additional data which is necessary for classification of complex landscape. Rizvi and Mohan (2012) reported analysis of WV-2 imagery using the
OBIA approach. Urban landscapes are a unique combination of natural and built environments. There is relatively high local variance due to which it is a challenging task to classify the image.

3. Methodology

3.1 Rule set method

In rules of CNL parameters and thresholds are determined by combining expert knowledge, quantitative statistics and trial and error. The associated rule set is composed of a series of logical steps that are built on imagery.

3.1.1 Separate vegetation area:

To strengthen the spectral power of imagery for vegetation extraction NDVI (Normalized Difference Vegetation Index) (eq.1) is computed as a separate band.

\[
NDVI = \frac{NIR - Red}{NIR + Red}
\]  

A prerequisite to classification is image segmentation. Image objects are building blocks for further classification or other segmentation processes. They are serving as information carriers. Each object has large number of characteristic properties. Number of possible features associated with objects can be found in the Reference Book of Definiens eCognition Developer 8.7 (Definiens eCognition 2011). The best segmentation result is that which provides optimal information for further processing (Liu and Xia 2010).
Contrast split segmentation is top down segmentation which divides objects into smaller parts (Gonzalez and Woods, 2007). It is most convenient segmentation algorithm for separation of vegetation and non-vegetation area as it segments the scene into dark and bright image objects based on a threshold value that maximizes the contrast between them. NDVI layer is selected for contrast split segmentation algorithm. As pixel level is selected as image object domain, it executes a chessboard segmentation of variable scale and then performs the split on each square. Other parameters used for contrast split segmentation are given in Table 1. By applying MRS algorithm most of the small trees are not segmented as a single object, but are included in larger segments of non-vegetation area or else it leads to over segmentation. To avoid such segmentation result contrast split is applied first. Hence isolated trees having contrast with background can be easily identified. Area and elliptic fit are the parameters used for classification. Objects of vegetation class which fulfil the threshold values are classified as isolated trees. To smooth the surface of isolated trees pixel based object reshaping algorithm is used. The classified image object and its relative area features are used to find the seed image objects to grow or shrink in specified area.

Table 1. Parameters used for Contrast Split Segmentation algorithm

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contrast mode</td>
<td>Edge Difference</td>
</tr>
<tr>
<td>Minimum relative area dark</td>
<td>0.1</td>
</tr>
<tr>
<td>Minimum relative area bright</td>
<td>0.1</td>
</tr>
<tr>
<td>Minimum contrast</td>
<td>0</td>
</tr>
<tr>
<td>Minimum object size</td>
<td>10</td>
</tr>
</tbody>
</table>

eCognition has the feature where unwanted area can be masked out to save the time of analysis and hence further analysis done on vegetation class only. Vegetation class consists of small trees, isolated trees, shrubs, grassland etc.
3.1.2 Separate grass from vegetation:

Multiresolution segmentation (MRS) is applied on remaining vegetation area to separate grass and tree clusters. Proper segmentation process gives objects which are more meaningful and easier to analyze. Hence it was tried with different segmentation algorithms and found that MRS is best suitable. Different weights are assigned to spectral bands which will further improve the segmentation result (Moskal et al. 2011). Higher the weight assigned to an image layer, the more weight will be assigned to that layer’s pixel information during the segmentation process. The scale parameter is an abstract term that determines the maximum allowed heterogeneity for the resulting image objects. Hence object size depends on scale parameter. Composition of homogeneity criterion depends on shape and compactness parameters.

Shape parameter defines weight of shape and color criterion when segmenting image. Higher its value lower will be influence of color on segmentation process. The bigger the Compactness weight is, the segmented objects are in more compact shape (Definiens eCognition 2011).

Vegetation has strong reflectance within NIR bands hence FCC is used as shown in fig. 1 (a). NIR 2 band is less affected by atmospheric influence as well as enables broader vegetation analysis. Red edge band can able to provide quantitative information on the health of the trees due to this more weights assign to those bands. Algorithm parameters used for MRS are given in table 2.

(a)  
(b)
Table 2. Parameters used for Multiresolution Segmentation algorithm on vegetation class

<table>
<thead>
<tr>
<th>Scale Parameter</th>
<th>Shape</th>
<th>Compactness</th>
<th>Band weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.2</td>
<td>0.7</td>
<td>Coastal blue (1), Blue (1), Green (1), Yellow (1), Red (1), Red edge (2), NIR1 (4), NIR2 (4).</td>
</tr>
</tbody>
</table>

On this segmentation result different feature values are calculated for image objects. The features which are providing best separation between classes are used for assigning class. Rare grass is not chlorophyll rich area also soil particles are present within that area. Mean of red band, NDVI, area are the features used for separating rare grass class. Dense grass is brighter compared to rare grass. Instead of taking the individual band values vegetation indices are used for classification purpose. Vegetation indices use combination of two or more wavelengths and gives effective way for determining type of vegetation (Raymond et al. 2013, Index Data Base-A database for remote sensing indices).

Canopy content chlorophyll index (CCCI) is used to separate out dense grass from vegetation class. This vegetation index is calculated by following formula. Some of the tree crowns are also misclassified as dense grass and those are removed with the help of area and standard deviation of NIR1 band. The surrounding area of dense grass which is missed out is added to the class with the help of contextual feature and region growing algorithm. The neighboring image objects which are spectrally similar with small difference in value of NDVI 2 are merged into dense grass area. While using the region growing algorithm threshold condition is defined for candidate class and those candidate objects which satisfy the condition are used for region growing.
3.1.3 Separate Tree clusters:

After grassland separation vegetation class is merged. From vegetation class small tree clusters are separated and morphological operations are applied on them. Morphology operations are used to smooth features, then all of the edges are dealt with by having objects from other classes consume them. Opening and closing are the basic morphological operations. Opening is defined as the area of an image object that can completely contain the mask. The area of image object that does not contain the mask completely is separated. The refinement of small tree clusters is done with opening operations. According to the width of image object circular masks are set.

3.1.4 Vegetation Below Shadow:

One more advantage of creating NDVI as separate band is that the vegetation area below shadow is also visible as shown in fig.1 (b). This is however not possible with false color
composite imagery. To do the analysis on vegetation area covered by shadow, preliminary requirement is detection of shadow. Several attempts have been carried out on the detection of shadow areas in satellite and aerial optical images. Shadow is detected with brightness value by applying proper threshold. However water and shadow both have similar brightness value. Land and water mask (LWM) is used to classify water and shadow area.

\[
LWM = \frac{\text{NIR 1}}{\text{Green}}
\]  

(5)

Applying MRS on shadow class only, we get image objects for vegetation below shadow. The parameters for MRS are given below in table 3. Scale parameter is kept small since extraction of small vegetation area is done. Combination of GRVI (Green Red Vegetation Index) and NDVI feature is used to classify the shadow area into vegetation below shadow which is visible only by NDVI band.

Table 3. Parameters used for Multiresolution Segmentation algorithm on shadow class

<table>
<thead>
<tr>
<th>Scale Parameter</th>
<th>Shape</th>
<th>Compactness</th>
<th>Band weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0.3</td>
<td>0.7</td>
<td>Coastal blue (0), Blue (0), Green (0), Yellow (0), Red (0), Red edge (1), NIR1 (1), NIR2 (1), NDVI (1), GRVI (2).</td>
</tr>
</tbody>
</table>

\[
\text{GRVI} = \frac{\text{Green} - \text{Red}}{\text{Green} + \text{Red}}
\]  

(6)

3.1.5 Creating separate region for complex areas:

In eCognition there is provision for creating regions as a domain and individual processing
only in the specified region. Within one project several regions can be created. The remaining vegetation area consists of tree clusters. Various tree species exist close to each other in a cluster. In the imagery a few regions have very low contrast between tree canopy and other vegetation. Such a specific region is selected and created a separate map for that region.

Analysis on separate map: Chessboard segmentation with object size 1 is applied on map. To extract the tree canopy seed pixels are selected first followed by region growing algorithm. The candidate class for seed pixels to grow can be selected by different ways. However Parent process object (PPO) which is part of process related operation is a well-known feature provided by eCognition. A special case of PPO is 0th order PPO in which more than one image object can be taken as input. In the newly created map seed pixels are those having maximum value of NIR1. This is done by find-domain-extrema algorithm. These seed pixels are grown into surrounding if difference between the parent and child is less than threshold value. So tree clusters are separated from other vegetation area having similar spectral properties. This new map is placed back on main project map by synchronize-map algorithm.

![Figure 2. (a) A subset of study area (Specific Region is created) (b) Segmentation result for specific region](image)
4. Results and Discussions

Quality of classification has to be assessed because up-to-date information comes from satellite images and this information can be input to GIS (Rizvi and Mohan. 2011). In this work authors used method of accuracy assessment based on samples. Samples for every class were drawn over the image by visual interpretation. Overall accuracy of 88.12% and Kappa Index of 0.85 were obtained using rule set method. Also per-class accuracy values are satisfactory and corroborate the made visual evaluation. Objects of small isolated trees and large isolated trees are classified as tree clusters which lead to error of omission. The error of commission is more for tree clusters which has decreased user’s accuracy in rule based classification. The numbers of small and large isolated trees are counted. Also total area under vegetation class is found out. The entire study area and classified image is shown in Figure 3 and Figure 4 respectively.

Table 4. Classification accuracy for rule set method

<table>
<thead>
<tr>
<th>Accuracy</th>
<th>Dense grass</th>
<th>Rare grass</th>
<th>Tree Clusters</th>
<th>Small isolated trees</th>
<th>Large isolated trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer</td>
<td>0.846</td>
<td>0.928</td>
<td>0.9</td>
<td>0.875</td>
<td>0.857</td>
</tr>
<tr>
<td>User</td>
<td>0.916</td>
<td>0.812</td>
<td>0.818</td>
<td>1</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Overall Accuracy 0.881  KIA 0.849
5. Conclusion

The study demonstrates that OBIA is a powerful analysis method for information extraction from high resolution satellite imagery. Combination of different vegetation indices and segmentation algorithm improves efficiency of classification. This approach not only overcomes the drawbacks of pixel based approach but also replicates the human visual interpretation in the results. Processing of large area is possible with ease and low cost. The information from this analysis is helpful for municipalities to plan for tree plantation program also to assess the impact of housing constructions etc. Further improvement in the results can be done with LIDAR data which provides height and intensity parameters.

References


Index Data Base-A database for remote sensing indices, http://www.indexdatabase.de/db/is.php?sensor_id=40


