Object-Based Image Analysis: Study of urban land cover classification in the city of Campinas-SP

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Abstract—**Classifiers that make use of pixel-by-pixel approaches are limited in the high spatial and radiometric resolution of intra-urban regions. That happens because of noise in the image and confusion in the targets spectral response that display similarity in it's signal like: ceramic roofs and bare soil. Because of that, the literature favors approaches that make use of object-oriented analysis for image segmentation, those approaches make a better use of the high spatial resolution and don't use only the target's spectral response. Assuming that the object-oriented analysis is a favorable approach to be implemented in intra-urban areas, this paper will assess the results of such approach through an implementation of it in an urbanized area from the city of Campinas (Brazil), which has a size close to twelve square kilometers. Making use of the fusion of high spatial resolution image from Worldview-2 sensor and it's panchromatic band, the experiments were performed with the use of E-Cognition Developer 8™ as the segmentation platform, and the classification being based on a decision tree generated by C4.5 algorithm on the software WEKA. This work also assess which approach best suits the experiment needs, being an optimal attribute selection achieved through a Wrapper filter, with a final kappa statistic of 0.9425.**

I. Introduction

Data about the land cover mapping is not only a relevant factor for the evaluation of global change, it is also an essential product for governments cells regarding to decision making and research [1]. Efforts in the development of remote sensing techniques for semi-automatic or automatic mapping of those areas have intensified and became indispensable, mainly, on the investigation of the use and land cover impact, for instance, for the nature, wildlife and human life. However, automating this process is also problematic due the high spectral variation within a single class, and therefore, it is a scientific question still open.

Regarding the presence of settlements in areas of remote sensing data, characteristics such as texture, shape or contextual information is required to adequately describe these areas [2]. In developing countries, it is often possible to find areas with dense settlements, built illegally on areas of high slope, for instance, composed of plastics, wood, and many others capable of aggravating the situation of the local ecosystem [3].

Taking into account the peculiar characteristics of these intra-urban targets that the Object-Based Image Analysis (OBIA) was developed, based in accordance with the traditional technique of pixel-based image analysis [4] and established as a favorable method for classification of high resolution imagery [5]. While the traditional method of Pixel-Based Image Analysis (PBIA) is based on the information of each pixel, OBIA is based on information from a similar set of pixels, based on their spectral properties, often called objects (i.e. color, size, shape, and texture). The technique comprises modeling the knowledge of an specialist through a semantic network.

This paper explores and demonstrates the ability of object-oriented analysis classification of urban areas in the image, presenting, especially, the use of decision trees algorithms as the data mining tool. There are countless platforms[1] that support OBIA [6]. However, we chose to use the software eCognition™ Developer version 8.7 [7] for the processes of image segmentation and classification. In addition, was adopted an open source software called WEKA version 3.6 (Waikato Enviroment for Knowledge Analysis) [8], which provides the main techniques dedicated to the study of machine learning, thereby, the classification in this work can be refined through data mining algorithms like C4.5.

II. Theoretical foundation

The classification consists in categorizing the data in the images in different classes of patterns, so that it is assigned an identity or probability values for the data analyzed. These classes represent the features and ground targets, such as water, savannah, urban area, area of deforestation, among others. The classification is nothing more than the recognition of these groups, whose members exhibit common characteristics.

The image classification can be further categorized into supervised and unsupervised. At first in the supervised approach, the user defines a set of samples of the categories to be used in the classification and later, with computational resource, the image is processed. For each analyzed region, one class is associated to it. The unsupervised approach is useful when you do not have information about the classes in the image area.

Techniques for objects classification in remote sensing images are extensive and aggregate many branches of research, among those techniques the Object-Oriented Image Analysis (OBIA) is among the favored ones for high resolution spatial and spectral images. Some works in the literature [10] classify remote sensed data to identify different species of trees, using

[1]Platform comparison process can be viewed at: http://www.ioer.de/segmentation-evaluation/results.html. Access: September 2014

for this purpose, high resolution hyperspectral data[2]. And since the major concern of this work address at urban areas, the spectral separability between the targets is a factor of major relevance due to the heterogeneity of targets on the scene.

III. Materials

In this work, a multispectral scene from the Worldview-2 sensor was used. The data had 1.85m of spacial resolution, operating in 8 spectral bands (coastal blue, blue, green, yellow, red, red edge, NIR-I, NIR-II) acquired on December of 2013, along with a panchromatic image with spatial resolution of 0.50m. The region approached in this study is located in the southeastern State of So Paulo (Figure 1), in the city of Campinas, within coordinates -22.8135S and -47.0762W, with a total surface amounts approximately to $795km^2$, being composed of $238km^2$ of urban area with a population around 1.100.000 inhabitants (Figure 2).

In order to combine the advantages of the multispectral image with the fine spatial resolution of the panchromatic band, the fusion process is normally performed, also adopted in this work. For this purpose, the software ENVI [11], version 4.7, was used. It was also used the eCognition$^{\text{TM}}$Developer [7] version 8.7 for the segmentation and land cover classification. To achieve a consistent classification, it is necessary to choose the attributes which could contribute more in the discrimination of classes to be classified. In order to improve the accuracy of the classification, a data mining algorithm could be applied to select the best of these parameters. A list of attributes presented to the data mining algorithm is detailed in the next section. The software WEKA 3.6[3], mentioned in the Section I, is an open source software that provide a complete collection of machine learning algorithms for data mining, then, selected for this task.

IV. Methods

To improve the spacial resolution of the image a Principal Component Analysis (PCA) approach where implemented with the panchromatic band image acquired from WorldView-2 with it's respective multispectral bands. The software of choice for this task was ENVI 4.7, and this procedure is called Principal Component Spectral Sharpening (PC Sharpening) in it. To perform a PC multispectral data transformation in ENVI, first the PC band 1 (PC1) is replaced with the high resolution panchromatic band, then, the panchromatic band is rescaled to the same size of the PC1 so that no distortion of the spectral information occurs. The PC spectral sharpening approach assumes that the PC1 is a good estimation band of the panchromatic data. The data now passes through a inverse transformation, resampling the multispectral data to the high resolution pixel size using a nearest neighbor, bilinear or cubic convolution technique [12].

[2]The hyperspectral data allows, among others, the best spectral description of the targets concerning its physico-chemical and biological properties

[3]Available on: http://www.cs.waikato.ac.nz/ml/weka/

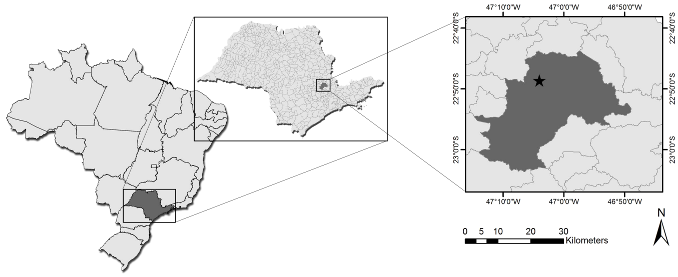

Fig. 1. Study area: Municipality of Campinas-SP.

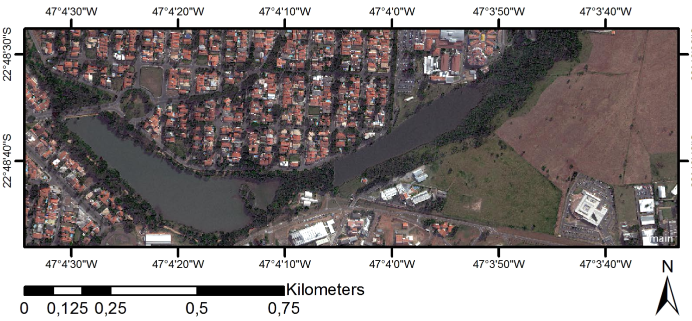

Fig. 2. Worldview-2 subset scene. Color composite R(5), G(3), B(2)

A. Segmentation

In the object based image classification, the segmentation is the first step of the process to generate the segments that will be later classified [13]. In the segmentation process it is also possible to implement a multiresolution approach, which consists of analyzing smaller objects in a higher resolution and bigger objects in a coarser one. In the case of the eCognition system, it implements a multiresolution based segmentation that includes several parameters defined by the user [15] like compactness, suavity and scale. In this work the parameters where arbitrarily chosen to best fit the needs of the classification process, being it's values compactness = 0.5, scale = 12, shape = 0.1, and the default band weight of 1 to all the bands of the multispectral image, respectively.

B. Data Mining and the Decision Tree Algorithm

A decision tree is a structure in which each internal node of the tree represents a decision on which the parent node determines which attribute will flow to its child node. To classify an object, the process starts at the root of the tree. The decision assess the attributes associated with that node and selects the branch of the tree whose test was positive repeating the process until it finds a leaf that indicates the class to which the object belongs.

One of the most important parts of the decision tree generation process is to search for the most significant attributes for the data mining. Because of that, numerous algorithms in order to automatically select the best-fitting attributes for data mining process have been implemented. Among the several available feature selection methods, the one that is worth to be cited would be the wrapper method [16], which considers the calculation of scores for a certain subset where the subset with best score (highest hit rate) is selected. Also implemented in this work was the CFS method (Correlation Feature Selection) [17], that, on the other hand, ranks a set of randomly chosen attributes according to a measure of correlation referred merit. The higher the merit value, the greater the correlation between the classes will be. The method ends after the search of the best merits of new data sets, selecting the best among them.

Although the wrapper method presents smaller computational performance, it is still considered the best attribute selector. And in order to evaluate the selector methods, three data mining processes will be carried out: Wrapper, CSF algorithms and manual empirical selection. After filtering the attributes to be used in data mining, the decision tree generation process can be carried on. The sorting algorithm for decision tree used was the J48, a JAVA transcription of the original C4.5 algorithm implemented in WEKA.

C. Object-Oriented Image Analysis

In the paradigm of Oriented-Object (OO), the object means an instance of a class, which is the representation of a set of objects with common characteristics called attributes. Each class handles its attributes through its methods, and these are also part of the set. Thus, a single class in oriented-object represents a real world object, such that the attributes of this class are their characteristics, and methods, its actions or intrinsic behavior, able to change its state (attributes) or the state of other class. In this context, imagine a set of classes representing each object in the real world, modeled as the actions which integrate them with each others. Thus, it is possible to establish a connection between one or more classes, for instance, the important concept of generalization, which allows a class (subclass) "inherit" attributes and functions previously attributed only to another class (super-class).

In remote sensing, the term Object Based Image Analysis (OBIA) was a new terminology adopted by the community to differentiate applications using the technique in this area from other areas, for example, computing or related areas. The OBIA was used for the first time in 90, since then, it has increased in remote sensing, and has been the subject of study in many of scientific papers. From 2000, the term OBIA gained some popularity after one of the first commercial software aimed at the analysis of remote sensing images, eCognition.

In OBIA, the knowledge is expressed by a semantic network, so that each class obeys hierarchical levels associated with objects that represent each image. The literature describes the role of pixels within the object-oriented paradigm, such that this has no direct relationship with or semantic scene targets, moreover, does not allow the extraction of attributes, as opposed to a segment or region. [18] Thus, a segment or region on the scene is called object in OBIA, representing a unit for classification.

V. RESULTS

A. Data mining and Classification

The CSF and Wrapper filters were applied to a set of 417 attributes, where the CSF filter selected 6 atributes and the Wrapper approach had selected 35. The resulting values from the application of the respective filters are presented in Table V-A and since the wrapper filter displayed a better Kappa, it was therefore used for data mining process. Both the attributes and the decision tree obtained in the classification by J48 implementation of the C4.5 in WEKA can be viewed on 3.

```
(Brgt+B)-Edge <= 39.314791
|   Ratio to scene Layer 5 <= 0.995797
|   |   Ratio to scene Layer 5 <= 0.551766: Arboreous vegetation (11.0/1.0)
|   |   Ratio to scene Layer 5 > 0.551766: Low vegetation (18.0)
|   Ratio to scene Layer 5 > 0.995797
|   |   Ratio Layer 3 <= 0.135216: Ceramic roof [Red] (14.0)
|   |   Ratio Layer 3 > 0.135216: Exposed soil (16.0)
(Brgt+B)-Edge > 39.314791
|   (Brgt+B)-Edge <= 50.674699
|   |   Ratio to scene Layer 5 <= 0.810638
|   |   |   GLDV Mean (quick 8/11) (45°) <= 1.126131: Lake (9.0)
|   |   |   GLDV Mean (quick 8/11) (45°) > 1.126131: Shadow (11.0)
|   |   Ratio to scene Layer 5 > 0.810638
|   |   |   Ratio Layer 8 <= 0.10026: Road (13.0)
|   |   |   Ratio Layer 8 > 0.10026
|   |   |   |   Ratio to scene Layer 5 <= 1.659925: Ceramic roof [Dark] (7.0)
|   |   |   |   Ratio to scene Layer 5 > 1.659925: Ceramic roof [Bright] (9.0)
|   (Brgt+B)-Edge > 50.674699
|   |   Ratio Layer 8 <= 0.073405: Pool (12.0)
|   |   Ratio Layer 8 > 0.073405: Metalic roof (15.0)
```

Fig. 3. Decision tree automatically generated by the J48 algorithm in WEKA

Results of the selectors CSF and Wrapper.

Selector	Relative absolute error (%)	Attributes	Kappa Statistic
No Filter	15.561	417	0.8443
CSF	9.009	35	0.9098
Wrapper	6.4701	6	0.9425

A confusion matrix is also generated by this process and can be visualizes on the Table 4. The values presented on this table shows the confusion between all the available classes in the experiment, where it is possible to note a confusion between several classes, like: Low Vegetation and Arboreous; Shadow and Low Vegetaion; Ceramic roof [Red] and Bare soil; Ceramic roof [Bright] and Bare soil; Ceramic roof [dark] and Road.

The results shows there were confusion between the bright, regular and dark ceramic roof classes with the bare soil class. Most probably because of the similarity of its spectral response due to its chemical composition and physical characteristics. Another confusion on the classification was between the classes Lake and Shadow, also, both has a similar spectral signal, absorbing most of the incident radiance on them, that would also contribute to mistakes on dark regions of the scene. Pools and Metallic roof also presented some confusion. The final result of the classification process can be seen on Figure 5, being worth of notice the missclassifications nearby the margins of the river. That kind of mistake could be easily fixed with some simple sets of rules on the eCognition platform, but the fix wasn't implemented since the purpose of the work was to assess the attribute selection filters.

A	B	C	D	E	F	G	H	I	J	K	Class
18	0	0	1	0	0	0	0	0	0	0	**A** - Ceramic roof [Bright]
0	14	0	0	0	0	0	0	0	0	0	**B** - Ceramic roof [Red]
0	0	12	0	0	0	0	0	0	0	0	**C** - Pool
0	0	0	15	0	0	0	0	0	0	0	**D** - Metallic roof
1	0	0	0	15	0	0	0	0	0	0	**E** - Exposed soil
0	0	0	0	0	17	0	0	1	0	0	**F** - Low vegetation
0	0	0	0	1	0	5	1	0	0	0	**G** - Ceramic roof [Dark]
0	0	0	0	0	0	0	13	0	0	0	**H** - Road
0	0	0	0	0	0	0	0	10	0	0	**I** - Arboreous vegetation
0	0	0	0	0	1	0	0	0	11	0	**J** - Shadow
0	0	0	0	0	0	0	0	0	0	8	**K** - Lake

Fig. 4. Confusion Matrix - Filter: Wrapper.

Fig. 5. Final classification results obtained through the implementation of the decision tree using J48(C4.5) on WEKA over the segmentation generated by eCognition.

VI. Conclusion

The following work had as it's purpose to evaluate the contribution of the filter algorithms to the final image classification, using the kappa index as it's assess method. Through the several experiments performed over the same sample data sets, it was possible to notice on Table V-A a difference of $0,0327$ in the kappa index from the Wrapper filter approach to the CSF. That difference between the two automatic methods Wrapper and CSF makes it possible to infer that in this experiment, the Wrapper approach is best suited for attribute selection than the CSF, but the human attribute selection approach ain't going to be compared to the automatic methods because of its variability and somewhat empirical methods.

Regarding the results of the classifications, both filters Wrapper and CSF generated the same decision tree as an output, thus, making the same classification over the segments. Which isn't the case compared to the manual selection approach, that even thought it's generated kappa index being $0,0655$ below the CSF approach, it didn't generated confusion between the lake and shadow classes.

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