OBJECT ORIENTED CLASSIFICATION - A COMPARATIVE STUDY OF TWO ENVI FEATURE EXTRACTION METHODS

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Abstract: *Being considered a process that requires fewer resources, extracting features of interest from satellite imagery may prove to be an alternative that can provide good results while have a low production cost and high applicability. This study aimed to analyze two Objects Oriented Classification methods implemented on ENVI software to suggest which method is much feasible in classifying a satellite image of a complex urban area. To achieve the best result in the classification process were used ancillary data (nDSM, indices and masks). Based on the results: accuracy, visual inspection, time spent for each classification process, resources cost, etc., the ENVI classification methods showed they're power in thematic maps production.*

Keywords*: ENVI, Feature Extraction, Object Based Classification, Segmentation.*

1. Introduction

The high resolution space imagery from new generation sensors made remote sensing technology more attractive, providing new opportunities for potentially more detailed mapping and more accurate land cover area estimation than medium and low resolution images.

Urban environment becoming more complex and heterogeneous make the feature extraction process to be more challenging. While many researchers has focused on developing, adapting and applying these approaches, less attention has been devoted to the interplay of spectral data source (imagery), feature extraction methods, and geographic characteristics of the area under analysis (Freire *et al*., 2010).

Image classification is the process used to produce thematic maps from satellite imagery. The themes can range from categories such as: soil, vegetation, surface water, in a general description of a rural area to different types of soil, vegetation, and water depth or clarity for a more detailed description.

Being considered a process that requires fewer resources, extracting features of interest from satellite imagery or classification may prove to be an alternative that can provide good results while having a low production cost and high applicability.

The objective of this study is to discover which of the two ENVI Feature Extraction methods (Example Based and Rule Based) offers the most accurate thematic map by classifying high resolution satellite imagery. Based on Schovengerdt (2007), a thematic map shows the spatial distribution of identifiable earth surface features; it provides an informational description over a given area, rather than a data description.

ENVI Feature Extraction is a module (implemented in ENVI software) for extracting information from high-resolution satellite imagery based on spatial, spectral, and texture characteristics. This module offers tree types of mapping (Segment an image into polygons, Example Based classification and Rule Based classification). The first method doesn't offer a thematic map; it just segments an image into recognizable objects and exports them as shapes.

The Example based and Rule based methods are used for thematic mapping, change detection, feature extraction, etc.

2. Materials and Methods

2.1. Study area.

The study area, located within the Lisbon Municipality, has a square shape with an area of approximately 570 ha (approximately 2.4 km x 2.4 km).

The satellite data consist in one pan-sharpened QuickBird image dated 13 April 2005, with a spatial resolution of 0.6 m. The image has been orthorectified with sub-pixel accuracy, using Rational Polynomial Coefficients (RPCs) with 29 GCP's and validated with 22 checkpoints. For orthorectification, a Digital Terrain Model (DTM) was generated from the 1998 municipality vector cartographic map at scale 1:1 000 with a spatial resolution of 0.5 m. A LiDAR Digital Surface Model (DSM), provided by LOGICA in 2006, with a 1-meter spatial resolution, with an average measurement density of 20 points per m^2, was used as ancillary data.

For the classification process and extracting of feature of interest the software that was used is ENVI 5.1. Quantum GIS 2.0.1 was used for extracting polygons from classification results and use them as masks. For confusion matrix the polygons were selected using Arc GIS 10.2 with an external plugging for the toolbox to get "a random selection process" for a specified number of polygons. The SAGA GIS software was used to create the nDSM file by subtracting DTM file from DSM file.

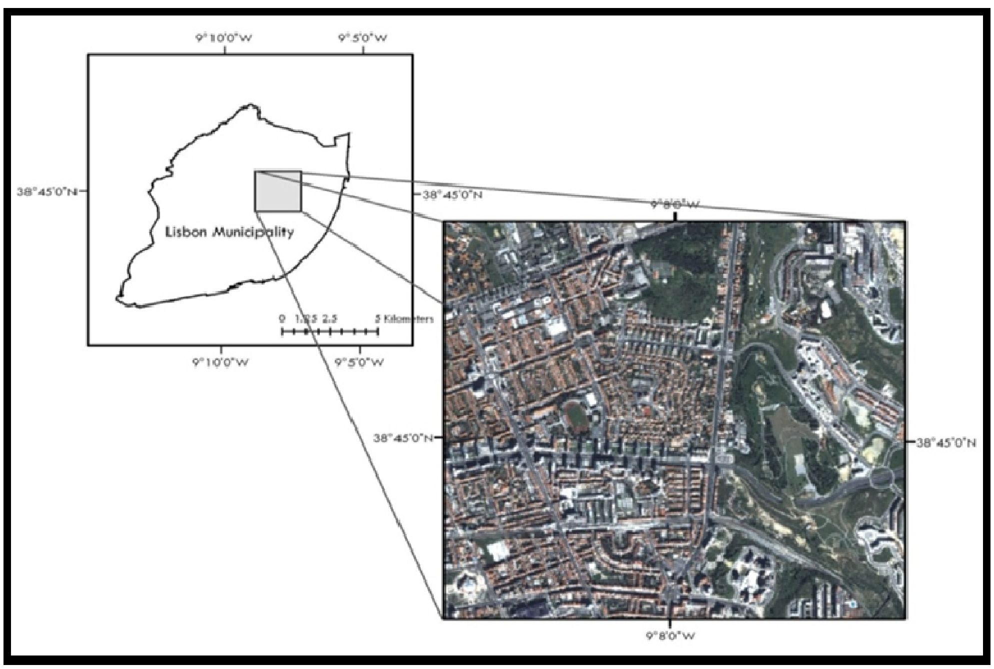

Fig. 2.1. Lisbon study area

2.2. Creating indices and ancillary data.

Pre-processing of data for the present study has included orthorectification and pan sharpening of imagery, computing ancillary data (Indexes and nDSM). The indices were created in ENVI with Band Math module using the formulas from the table 2.1.

Tab. 2.1. Formulas for indices.

Index name	Formula	Reference
BAI (Built up Area Index)	$BAI = \frac{B - NIR}{B + NIR}$	Bouzianiet al. (2010).
SI (Shadow Index)	$SI = \frac{R + G + B + NIR}{4}$	Bouzianiet al. (2010).
SE (Shadow Enhancement)	$SE = \frac{G - B}{G + B}$	- Test index
RRR (Red Roof Remove)	$RRR = \frac{R - B}{R + B}$	- Test index
NDVI (Normalized Difference Vegetation Index)	$NDVI = \frac{NIR - R}{GNIR + R}$	Rouseet. al. (1974).
EVI (Enhanced Vegetation Index)	$EVI = 2.5 * \frac{NIR - R}{NIR + 6 * R - 7.5 * B + 1}$	Liu and Huete (1995)
SAVI (Soil Adjusted Vegetation Index)	$SAVI = \frac{NIR - R}{NIR + R + L} * (1 + L)$	Huete (1998) Where L = 0, 0.5, 1
GSAVI (Green Soil Adjusted Vegetation Index)	$GSAVI = \frac{NIR - G}{NIR + G + L} * (1 + L)$	Sripada et al.(2006) Where L = 0.5
OSAVI (Optimized Soil Adjusted Vegetation Index)	$OSAVI = \frac{NIR - R}{NIR + R + L} * (1 + L)$	Rondeaux et al., (1996) Where L = 0.16
TSAVI (Transformed Soil Adjusted Vegetation Index)	$TSAVI = [a * \frac{NIR - a * R - B}{[1.2 * NIR + 2 - (c * b) + X(1 - a^2)]}$	Baret et al., (1989) Where: a = 1.2;b = 0.4; X = 0.8
Corrected Transformed Vegetation Index	$CTW = \frac{NDVI + 0.5}{ABS(NDVI + 0.5)} * \sqrt{ABS\,(NDVI + 0.5)}$	Perry and Lautenschlager (1984)

Because the study area contains not only buildings and transport units, as a majority of discriminate elements, but also vegetated areas (golf course in the east part, shrubs and trees in the north part, near the Lisbon airport) it was necessary to build a mask, based on the Normalized Difference Vegetation Index (NDVI), for vegetated areas to exclude non-vegetated areas. Using this methodology, 8 classes were extracted from the satellite image (Buildings, Bare soil, Shadows, Water, Transport units, Grass, Shrubs and Trees).

2.3. Feature extraction workflow.

The methodology which ENVI Feature Extraction module uses for the Object Based classification process is described in figure 2.2.

Both type of classification uses this workflow, just the classification methods were different.

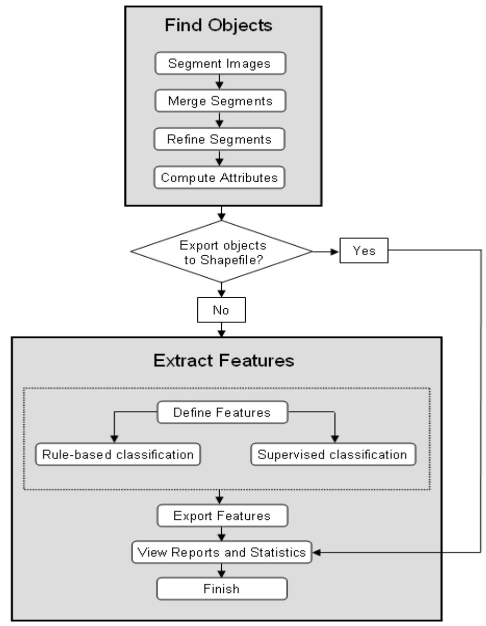

Figure 2.2. Feature Extraction Workflow

2.4. Feature extraction – Example based classification.

Because this image have urban zones in most of areas, for the segmentation was used the EDGE Algorithm with a scale level of 40, for the polygon merge was used Full Lambda schedule Algorithm with a 90 merge parameter for the R, G, B, NIR bands (Fig. 2.3).

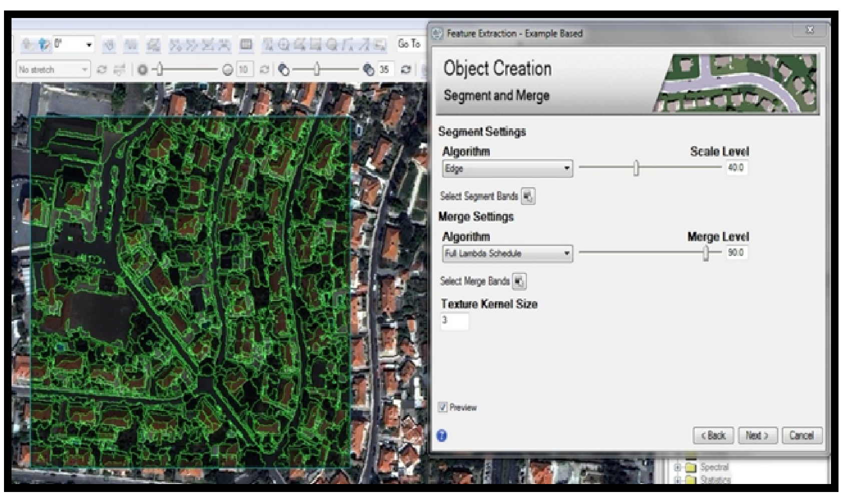

Figure 2.3. Image segmentation workflow.

The classes and the number of training areas (samples), used in this study were: Buildings = 380, Transport units = 314, Shadows = 322, Bare soil = 206, Water = 7, Grass = 286, Shrubs = 96, Trees = 353 (Fig. 2.4).

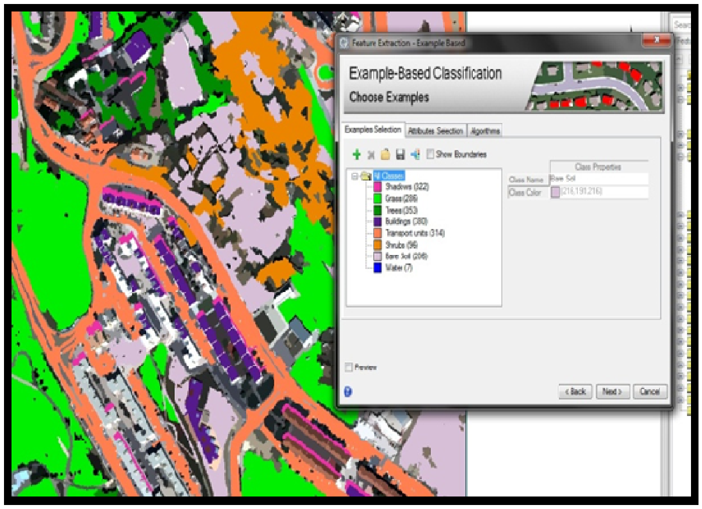

Figure 2.4. Example Based Classification Workflow

All the training areas were selected manually, from different zones of the image and with different texture to define the range of a class. The classification method was KNN (K Nearest Neighbor) which classifies segments based on their proximity to neighboring training regions.

2.5. Feature extraction – Rule based classification.

Rule Based Classification is based on computing different attributes for the segments and computing rules to classify the feature of interest, fig. 2.5. For a better discrimination between the classes, each class (from the total of 8) was classified separately.

This method conducts the classification process to a better discrimination between the classes. The segmentation workflow was similar to Example Based classification, just the parameters were different; separate parameters for each class (features).

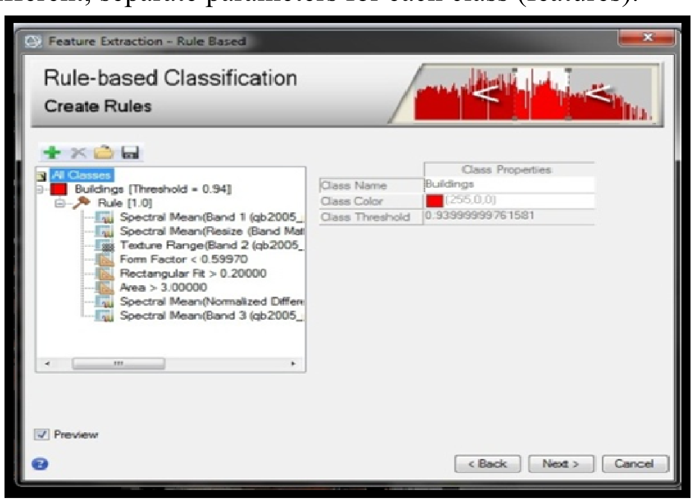

Figure 2.5. Example of rules for Buildings class.

3. Results and discussions

The classifier performance depends on the data that enter in the classification process (training areas and parameters knowledge). If the classes have clear boundaries (are clearly delineated) the result will be almost the same for different methods and software.

The study zone has also an impact in the classification process. The fact that the zone included not only buildings and roads, but also vegetation, bare soil and water, the main problem that classification had was in discrimination of vegetated areas where the ancillary data were a necessity.

The accuracy of the final result, the thematic map, is verified based on the confusion matrix. The confusion matrix is detailed in table 3.1. The classified maps are showed in fig. 3.1.

Tab. 3.1 - Error matrix and: user, producer, and overall accuracy and Kappa coefficient.

Classified data	Example based - Reference data									User accuracy %
	BS	BU	TU	SH	W	GR	TR	SR	UN	
BS	04631	246	10476	0	0	2173	0	0	0	**94.07**
BU	9063	11384	0	0	0	0	0	0	0	**92.63**
TU	9501	975	53477	664	0	5655	0	0	0	**96.95**
SH	2444	847	2265	42121	0	0	0	0	0	**96.95**
W	0	0	0	0	2638	0	0	0	0	**100**
GR	3763	2583	0	0	0	1355	1256	5426	0	**68.66**
TR	0	902	0	0	0	4800	6426	7481	0	**82.98**
SR	0	0	0	0	0	3488	1274	5762	0	**92.37**
UN	986	3924	0	0	0	3855	0	1129	286	**2.78**
Producer accuracy %	**88.44**	**89.47**	**97.67**	**97.67**	**100**	**85.5**	**96.21**	**47.2**	**50**	**-**
Overall accuracy = 88.8907%						**Kappa coefficient = 0.8528**				

Classified data	Rule based - Reference data									User accuracy %
	BS	BU	TU	SH	W	GR	TR	SR	UN	
BS	9478	0	0	0	0	0	0	0	0	**100**
BU	0	2458	0	3	0	0	0	0	0	**99.99**
TU	0	0	6986	0	0	0	0	0	0	**100**
SH	0	0	0	436	0	0	0	0	0	**100**
W	0	0	0	0	243	0	0	0	0	**100**
GR	0	0	0	15	0	998	0	0	0	**99.85**
TR	0	0	187	224	0	60	738	0	0	**94.01**
SR	0	0	0	6	0	0	0	2177	0	**99.97**
UN	0	0	0	4518	0	0	0	0	261	**36.69**
Producer accuracy %	**100**	**100**	**99.73**	**47.79**	**100**	**99.40**	**100**	**100**	**100**	**-**
Overall accuracy = 96.8172%					**Kappa coefficient = 0.9574**					

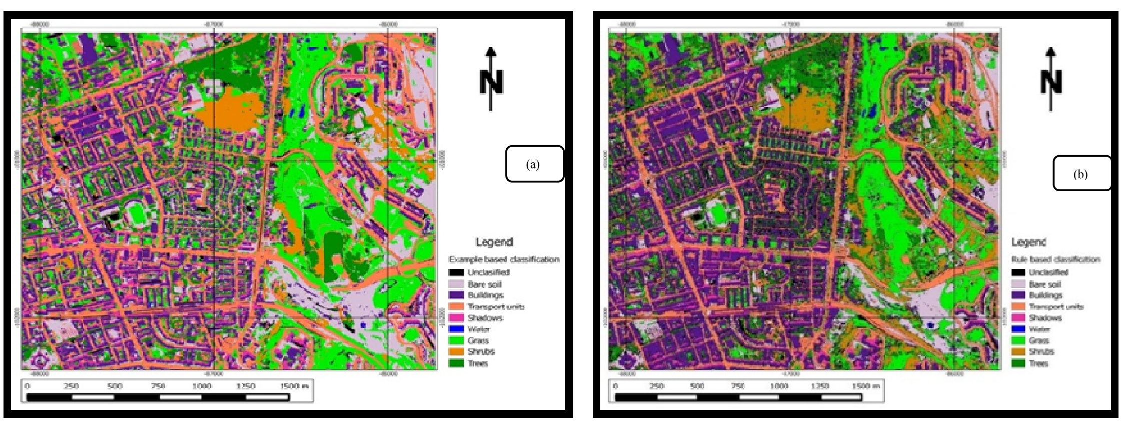

Fig. 3.1 – Example Based classified map (a), Rule Based classified map (b).

Legend: U – Unclassified; BS – Bare Soil; BU – Buildings; TU – Transport Units; SH – Shadows; W – Water; GR – Grass; TR – Trees; SR – Shrubs – (same classes with same colours for both maps).

Most problems appeared in vegetated areas where “Grass” and “Shrubs” were confused with “Trees”. The location of shadows had also a great impact in the classification process. For the shadows which fall over a vegetated area with a high density, the NDVI value was different compared with other areas with same type of healthy vegetation. Also, the other characteristics (texture, indices values) are different and this caused cause misclassifications between the vegetation classes.

The quality, composition and degree of use of the asphalted roads have also influenced the classification process making the algorithm to confuse the roads with shadows.

The black zones are areas that algorithm couldn’t classify as a class and they remain unclassified and were put in the class “Unclassified”.

4. Conclusions.

For a satellite image, using same training areas and two or more classification methods, it can be said that a method offered a better result than another, but only in that situation. It should not be generalized, because some classification methods need more or less intervention from the operator. Based on this intervention and operator knowledge of the methods and parameters some classification could provide a better result comparing to another.

Being considered the limitations which Example Based Classification had (segmentation and classification for all classes in the same classification process, ancillary data for all classes in the same workflow) the classified (thematic) map obtained is better than most of the pixel based classification algorithms can offer. This method can be used to classify a satellite image into multiple classes in a single workflow offering a good result in a short time and with less intervention in the classification workflow.

The classified map obtained with the Rule Based Classification, compared with Example Based classification, offered a better result. Adding ancillary data in the classification process showed a better approach to the reality. The possibility to classify only a class in a single workflow had also a great impact in the final result offering some black or overlaying zones but a better accuracy of the features. For extracting only a type of feature, or for classifying a satellite image, this method would be a great choice even for an inexperienced user.

The Rule Based Classification proved to be the best method for classifying or for extracting a feature of interest from an urban satellite image but is a time costing method. For a shorter time and with a lower accuracy the Example Based Classification would be the best choice. Using a satellite image of a dense urban area could be a challenge for both type of classification in the offering the best classification result.

The applied methodology used for this satellite image classification, combined with the ancillary data added in the classification process, provided an overall accuracy ranging from: 89% to 97% which shows that ENVI have two powerful thematic mapping algorithms.

5. References

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