OBJECT ORIENTED CLASSIFICATION IN URBAN AREAS USING THE GEODMA PLUG-IN

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ABSTRACT:

The present study used the GeoDMA plug-in associated with the software Terra View and images from the optic sensor WorldView-2 to realize the land use and land cover classification in a test area of the city of São Luis (MA). Through GeoDMA, image segmentation through Region Growing algorithm was performed, which indicated better results before the realized tests. Further on, the spectral and form features permitted by the software were extracted for the 8 used bands. The collection of the same number of samples for each of the defined classes on the image permitted the decision tree algorithm C4.5 to realize the classification of the image. The methodology proposed is efficient for the classification of complex urban areas in high resolution images once the classification resulted in a Kappa index of 0,72. The present study approached the functionalities of the GeoDMA plug-in presenting potentialities for object oriented classification.

1. INTRODUCTION

Among land environments, the coastal areas have always been considered of great interest by the population due to the facilitation of relations between people from different continents, the accessibility of natural resources and strategic location. Therefore, the first clusters were formed, which evolved to consolidate important metropolises.

The coastal environments are considered sensitive for their dynamicity, dune presence, beaches, estuaries and mangroves. Due to anthropic intervention, this land portion has gained attention to the maintaining of its balance, having the studies in this area assist the regional and urban planning (FEITOSA, 1996).

Because of the great amount of information that can be extracted from the urban land use and land, Remote Sensing data are held as greatly important once it's unviable to acquire a large part of the information *in loco* since it constitutes long and expensive work (JENSEN; COWEN, 1999).

The urban areas are considered areas of difficult identification and detailing through images due to its spatial, spectral heterogeneity and small target dimensions (ALMEIDA et al., 2009). However, the technological advance permitted new orbital products to become more adequate for such studies due to resolution refinement, enabling bigger differentiation amongst the targets (ZHOU et al., 2006; MYINT et al., 2011).

With the objective of differentiating the automatic classifiers to work with new images, object oriented classifiers were developed, which assume new procedures, considering object delimitation through homogenous characteristics such as mean, variance, dimensions, form and texture BLASCHKE, 2010).

2. MATERIAL AND METHODS

2.1. Material

The present study used an image cut from the satellite WorldView-2, with its 8 multispectral bands on the Calhau neighborhood, north portion of the city of São Luís (MA).

Such cut was chosen due to the local heterogeneity, providing adequate scenery for the classification practice with vertical and horizontal land use type. The identified targets in this area were: sand, concrete, metal roofing, low vegetation, tree vegetation and others.

The procedure was conducted through the TerraView 4.1 software, along with Geographical Data Mining Analyst plug-in (GeoDMA).

2.2 Method

Once the classification is based on spectral and spatial characteristics, the present study used the 8 bands of WorldView-2 satellite. According to the conducted tests, better results were seen, comparing to procedures that used only 3 bands.

To guarantee good image classification, segmentation is of extreme importance. This way, based on tests, we opted for the use of the Region Growing algorithm (BINS et al., 1996) that groups pixels or sub-regions in bigger regions.

Since the used image is of high spatial resolution, the Euclidian Distance and Minimal Area parameters were of 150 and 30, respectively. These were established through preliminary tests, showing that several features presented better segmentation with these values.

Afterward, available spectral and form features were extracted using the GeoDMA plug-in. Following, the classifier was trained, through obtaining identical sample quantities of the classes mentioned before. We can highlight these classes were previously determined through image cut observation, on true color composition - 5(R) 3(G) 2(B).

For the classification procedure, all software extracted features were selected and the Tree Decision algorithm was used for the definition of image classification parameters. Subsequently, the validation of image classification was conducted through a confusion matrix along with the calculation of the Kappa concordance coefficient. This process was realized by comparing samples that weren't used on the training process with the final classification.

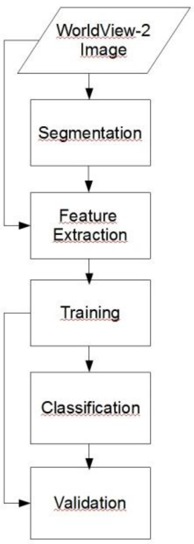

Image 1: Fluxogram of the used methodology.

3. RESULTS AND DISCUSSION:

Through the samples acquired on the training process, the polygon classification was realized, resulting on the decision tree we demonstrate on image 2.

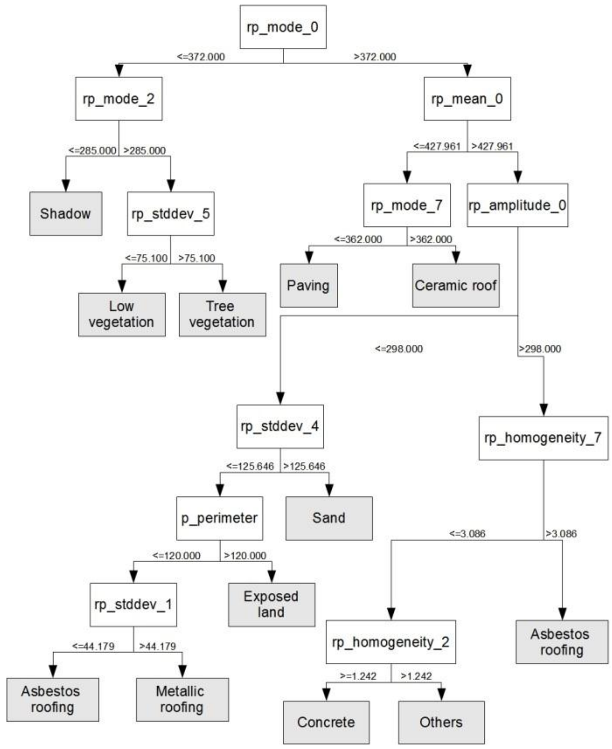

Image 2: Decision tree used for image classification

The decision tree obtained success when it incorporated key elements and important values for the pattern determination that allowed image classification.

The mode of spectral information of band 1 (rp_mode_0) was responsible for image differentiation in two blocks, being the first responsible for shadow classification, low vegetation and tree vegetation, and the second for the other classes.

The spectral mode of band 3 (rp_mode_2) with values lower or equal 285 were classified as shadow, and the standard deviation of band 6 (rp_sttdev_5) was responsible for the low vegetation classification for values lower or equal to 75, and tree vegetation for values over 75.

The spectral mode of band 8 (rp_mode_7) permitted the classification of the classes paving and ceramic roofing while perimeter form was responsible for the definition of exposed land.

The spectral standard deviation of band 2 permitted to distinguish the classes asbestos roofing and metallic roofing while the standard deviation of band 5 permitted the classification of sand.

The spectral homogeneity of band 8 realized the classification of asbestos roofing, and of band 2 the definition of concrete and others classes.

The classification realized by the decision tree algorithm was evaluated through random samples collected in each class, being independent from the samples used during the training process. The evaluation resulted on a Kappa index of 0,72 which can be observed on table 1.

Table 1: Confusion matrix

Classified \ Reference	Sand	Concrete	Others	Paving	Exposed land	Shadow	Asbestos roofing	Ceramic roofing	Metallic roofing	Low vegetation	Tree vegetation
Sand	4	0	0	0	3	0	0	0	1	0	0
Concrete	1	7	2	1	0	0	0	0	0	0	0
Others	0	0	7	0	0	0	1	0	0	0	0
Paving	0	2	0	8	0	0	0	0	0	0	0
Exposed land	4	0	0	0	6	0	1	2	0	0	0
Shadow	0	0	0	0	0	10	0	0	0	0	0
Asbestos roofing	0	0	1	1	1	0	6	0	2	0	0
Ceramic roofing	0	1	0	0	0	0	0	8	0	0	2
Metallic roofing	1	0	0	0	0	0	2	0	7	0	0
Low vegetation	0	0	0	0	0	0	0	0	0	9	0
Tree vegetation	0	0	0	0	0	0	0	0	0	1	8

According to the Kappa index, and confusion presented by the matrix, we can see that the classification is considered reliable.

Based on this table, it’s possible to verify that some of these classes presented bigger difficulty of classification than others, for example sand and exposed land, metallic roofing and asbestos roofing.

Other classes were more adequately classified, such as paving class, which presented only two values confused with concrete class. It can be observed that shadow classification was realized adequately without error evidence.

Little confusion was found between the classes low vegetation and tree vegetation, once the algorithm considered important parameters such as mode of band 2 (blue) and standard deviation of band 5 (red) to differentiate them. The final result can be observed on image 3 along with the original image.

Observing both original and classified images, we can notice that, in general, classification was satisfying, mainly regarding paving, well delimitated throughout the cut.

Since it’s considered heterogenic scenery, with several types of targets, it’s important to highlight that some difficulties were found on the classification process. It was observed that, in dense areas, as the inferior portion of the image, which possesses great amount of residences, there was somewhat confusion for the classifier due to proximity and dimension of objects.

Still regarding this area, some houses presented in their interior leisure intended areas, such as backyards. Some of these backyards were classified as sand and vegetation, probably due to the presence of elements such as lighter floors of even gardens.

Another relevant fact observed was the great difficulty on the distinction between exposed land and ceramic roofing, seen mainly on the inferior right quadrant of the cut. Once the decision tree opted for differentiating them through mode, standard deviation and perimeter, attributes that could be relevant as form and homogeneity weren’t considered.

Another class that presented confusion to the classifier was asbestos roofing, once this presents similar attributes of texture, tone, coloring, brightness, form and localization comparing to paving, concrete and metal roofing.

Observing the final classification, it can be verified that the type of segmentation and its attributed values were very satisfying, once they generated polygons that respected similarity and adequately differentiated heterogenic areas.

4. FINAL CONSIDERATIONS

The present study showed that it's possible to realize the classification of a high quality image through the extraction of spectral and form attributes present on GeoDMA plug-in.

The object oriented classification, through the Decision Tree algorithm, guaranteed the construction of a classification complex enough to incorporate the key elements and important values for the determination of several classes.

It is important to highlight that though the partially satisfying result, due to classification confusion by the software, object oriented classification still represents better results in image classification and it is considered very important once it guarantees better distinction amongst targets by using information such as mean, variance, dimensions, form and texture of objects.

Thus, we can conclude that though there are still limitations, object oriented classification presents good results. The analyst knowledge is important both for the classification process and the editing of the said due to confusion among classes at the end.

The identification of land use in urban areas can certainly enrich municipal urban planning, providing better management especially in sensitive areas such as coastal regions.

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