PIMAR PROJECT - MONITORING THE ATLANTIC RAINFOREST REMNANTS AND THE URBAN GROWTH OF THE RIO DE JANEIRO CITY (BRAZIL) THROUGH REMOTE SENSING

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ABSTRACT:

The PIMAR Project - Program for Monitoring the Atlantic Rainforest Environment and Urban Growth of Rio de Janeiro through Remote Sensing, aims at the development of an operational methodology for monitoring the land cover dynamics on the borders between Atlantic rainforest remnant areas and urban areas in the city of Rio de Janeiro, Brazil. The project will aid the Government of Rio de Janeiro State in the implementation of actions against aggressions to those forested areas and in the definition of urban development and environmental planning policies. The basic input for the methodology is a sequence of stereo pairs of IKONOS images, from which both the vertical and horizontal growth of urban areas are being measured by visual interpretation on a multi-temporal basis. The PIMAR Project is currently evaluating the use of an automatic classification model as a way to accelerate land cover change information production to support decision making. This paper presents the first results obtained when applying the prototype of the model in the project's test-site. Such classification model has been developed and tested within the InterIMAGE system, which is an open-source knowledge and object-based classification system. The automatic classification model is being elaborated considering that an user would have only to collect samples of every land cover class to have, after running the model, the land cover map delivered. The presented prototype model uses the C4.5 algorithm, commonly used spectral features and a simple semantic net for performing the land cover classification of the test-site. The visual analysis and the global and per-class accuracy indexes suggest that the automatically made classification is satisfactorily accurate and has potential for significantly reduce the photo-interpreters work. A Global Accuracy of 81% was obtained as well as a Kappa Index of 0.61. Important classes Vegetated Areas and Urban areas achieved above 75% user and producer's accuracies.

1. INTRODUCTION

Over the last decades, the disordered and almost exponential sprawl of Rio de Janeiro city (Brazil) has been pressuring rainforest remnant areas on its borders. The horizontal growth of urban areas has been also suppressing rainforest areas on conservation units of great biological and ecological value. The lack of operational methodologies for obtaining up-to-date and reliable spatial information about the urban sprawl and forest suppression dynamics has until this moment hindered public organs actions and planning control.

The PIMAR Project (Remote Environmental Monitoring Program) consists in monitoring on a year basis the suppression of rainforest on conservation units inside the municipality of Rio de Janeiro through high resolution optical remote sensing. From a sequence of stereo pairs of IKONOS images, both horizontal and vertical growths of formal and informal dwellings are been detected and measured.

The PIMAR Project is currently evaluating the efficiency and accuracy of automatic classification methods as a way to speed up land cover change information production. This paper describes the automatic land cover classification model developed so far as a way to reduce and speed-up the photo-interpreters work. Such classification model has been developed using the open-source and free of cost knowledge and object-based classification system InterIMAGE (Oliveira et al., 2008).

No later than end of July 2010, the classification model will be implemented as a plug-in on the InterIMAGE system. That means that based on user-collected samples (a protocol for sample selection is also been written) the model will deliver the land cover classification of areas and dates that haven't been visually classified. The generated classification will be the input over which the photo-interpreters will work correcting misclassified segments and validating the automatically made land cover map. A reduction of 70 to 80% of the area to be checked by the photo-interpreters is expected.

Coordinated by the Laboratory of Geographic Information System (LabGIS) and by the Laboratory of Computer Vision (LVC) of the Pontifical Catholic University of Rio de Janeiro (PUC-Rio), the PIMAR Project has also the following objectives: (1) to develop reference-methodologies of manual and automatic land cover information extraction that could be applied in other areas and dates; (2) to provide fundamental spatial information that can support the definition of public policies within a sustainable perspective and guide specific punctual interventions; (3) to provide annually data and reports about the dynamic of rainforest suppression caused by urban sprawl or other factors with the intention to aware the population and hence enforce the public opinion; and (4) to evaluate the effectiveness of monitoring projects and intervention measures carried out by the Government of Rio de Janeiro State agencies.

2. TEST-SITE

The PIMAR Project is presently monitoring two important conservation units within the Rio de Janeiro municipality,

namely: the Tijuca National Park and the Pedra Branca State Park. For all this area a visual classification has already been carried out. In this study, however, we present the results obtained when applying the automatic classification model over a small section of the Tijuca National Park.

This area was selected as test-site of the project because of the noticeable sprawl of informal dwellings over legally protected natural areas (this is the area where the Vidigal Slum is located). Moreover, the area contents various instances of all land cover classes considered by the PIMAR Project. It was also considered in that decision the presence of social programs and projects in that area. Figure 1 shows the localization of the test-site in the state and municipality of Rio de Janeiro.
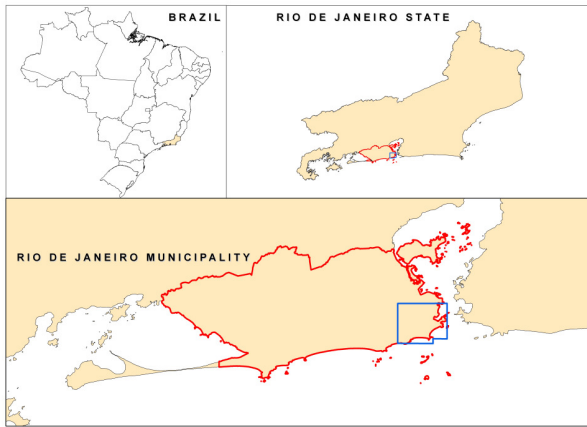

Figure 1. Localization of the test-site in Rio de Janeiro state and municipality. The blue line represents the bounding box of the IKONOS images used in this study.

3. MATERIALS AND METHODS

Pan-sharpened multispectral imagery from the IKONOS sensor were used in this work. The images have an 11 bits radiometric resolution (2048 gray levels) and are dated of March 3rd 2008. Obtained at 10 a.m. at low inclination angle the images have very good illumination conditions, which interfere significantly on the final results.

As for the software used, all image processing tasks were carried out in InterIMAGE system, with the exception of the application of the C4.5 algorithm (Quinlan, 1993) which, as explained below, was carried out in the platform Weka 3.7 (Weka, 2010).

For the horizontal urban growth measuring and land cover change analysis, the images of the project's first years of analysis (2008 and 2009) were segmented and the segments where visually classified by photo-interpreters participating on the project. Based on the manually made land cover maps, one can identify where and at what measure the vegetated areas (i.e. rainforest areas) were suppressed. For measuring the vertical growth of dwellings, the methodology described in (Brito et al., 2008) is being applied.

The automatic interpretation model was created and tested considering that a particular user, without necessarily having remote sensing or image processing knowledge, but necessarily with photo-interpretation experience, could apply the model and obtain the land cover classification map demanding from this user just the collection of samples for every land cover class accordingly to the sample selection protocol.

For all classes, the analysis units were segments generated by the Baatz and Shäpe (2000) algorithm. After consulting the literature and performing a few tests, the parameters set shown on Table 1 were chosen as universally applied for hypothesis of land cover objects (or sub-objects) generation. These parameters will always create small segments, as defined by the low scale parameter value, giving priority to color homogeneity instead of coherently shaped segments. The idea is to absolutely avoid that the segments disrespect the border between two different land cover objects.

Parameters	
Scale	20
Color	0.9
Shape	0.1
Compactness	0.5
Smoothness	0.5
Image layer weights (bands 1, 2, 3 and 4)	1,1,1,1

Table 1. Image segmentation parameters used for the automatic interpretation of the land cover.

When this model becomes operational, the user will need merely to click over the image collecting samples which are in fact segments generated with the above mentioned algorithm and parameters.

Num.	Feature
1	Area
2	Brightness
3	Max. pixel value of band 1
4	Max. pixel value of band 2
5	Max. pixel value of band 3
6	Max. pixel value of band 4
7	Min. pixel value of band 1
8	Min. pixel value of band 2
9	Min. pixel value of band 3
10	Min. pixel value of band 4
11	Mean pixel value of band 1
12	Mean pixel value of band 2
13	Mean pixel value of band 3
14	Mean pixel value of band 4
15	Std. Dev. of the pixel values of band 1
16	Std. Dev. of the pixel values of band 2
17	Std. Dev. of the pixel values of band 3
18	Std. Dev. of the pixel values of band 4
19	Ratio of band 1*
20	Ratio of band 2
21	Ratio of band 3
22	Ratio of band 4
23	Div. of the mean pixel value of band 3 by band 1
24	Div. of the mean pixel value of band 4 by band 3

Table 2. List of the samples features used for the decision tree inductions.

In this study we collected about 400 samples in an approximately 2 hours time. The rationale was to collect more samples of the most heterogeneous classes (i.e. with greater spectral and geometrical diversity) and fewer samples of the less heterogeneous classes. The considered classes and its descendent order of heterogeneity are: *Urban Areas*, *Bare Soil*, *Rocky Outcrop*, *Forest Trees*, *Grass Fields* and *Shadow*. All selected samples were exported together with twenty-four

spectral features and their respective class labels (Table 2). The samples and its features were then imported into the Weka 3.7 software.

After aggregating classes *Forest Trees* and *Grass Fields* into one class named *Vegetated Areas*, a decision tree was induced for the classification of classes *Vegetated Areas*, *Urban Areas*, *Bare Soil* and *Shadow*. A second decision tree was induced considering only classes *Forest Trees* and *Grass Fields*. Until that moment, class *Rocky Outcrop* was kept aside.

The next step was then to elaborate a semantic net for the automatic interpretation to be performed within the InterIMAGE system. After a few tests, the semantic net shown in fig. 2 was adopted.
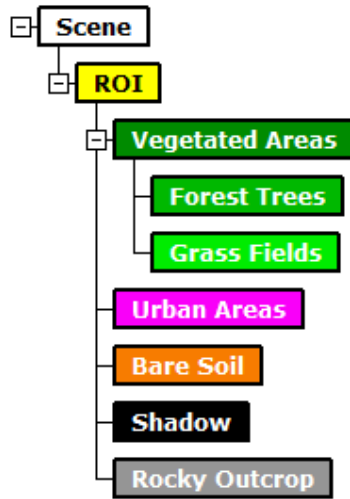

Figure 2. Semantic net elaborated for performing the automatic interpretation within InterIMAGE.

As it can be learned in (InterIMAGE, 2010), the interpretation strategy of the system has two steps: the *Top-Down* step (TD), where hypotheses of the occurrences of objects from the classes of interest are created, and the *Bottom-Up* step (BU), where, according to user-defined rules, these hypothesis are either partially or entirely discarded or validated into instances. Every node of the semantic net should have TD operators and BU rules. As we have a space limitation in this paper, we assume that the reader is familiar with the interpretation strategy of InterIMAGE and know the operators available in the system.

In the TD step, class *Scene* passes the whole image to be processed by the node *ROI* (using the *Dummy Top-Down* operator). This node imports the mask of the region of interest of the PIMAR Project (areas above 100 m height) using the *Import Shapefile* operator. Node *Vegetated Areas* also passes down to *Forest Trees* and *Grass Fields* the mask of the region of interest. These two nodes, along with *Urban Areas*, *Bare Soil* and *Shadow*, perform the segmentation of the images using the parameters shown on Table 1. We chose to extract *Rocky Outcrop* hypothesis slicing the slope image generated from a 10 m resolution digital elevation model, discarding the samples of this class. And thus ends the TD step and starts the BU step.

In the BU step the system will solve the spatial conflicts (i.e. cases where one geographic region is associated with hypotheses of more than one class) first between *Forest Trees* and *Grass Fields* (rule inserted into node *Vegetated Areas*) and

then between *Vegetated Areas* and all other classes (rule inserted into node *ROI*). The BU rule inserted into node *Vegetated Area* is actually the decision tree inducted for the classification of *Forest Trees* and *Grass Fields* (fig. 3). Likewise, the BU rule inserted into node *ROI* is the decision tree inducted for the classification of *Vegetated Areas*, *Urban Areas*, *Bare Soil* and *Shadow* (fig. 3).
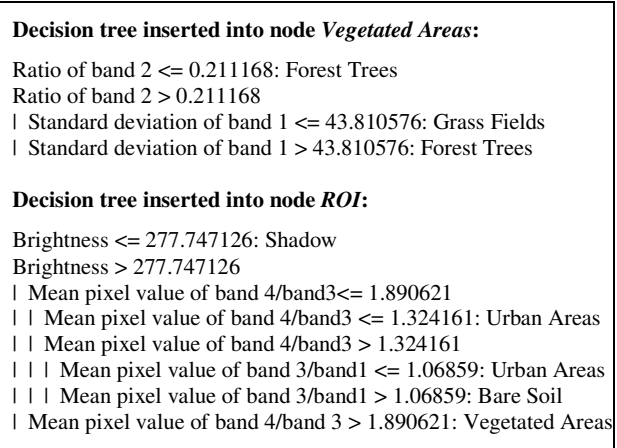

Decision tree inserted into node *Vegetated Areas*:

Ratio of band 2 <= 0.211168: Forest Trees
Ratio of band 2 > 0.211168
| Standard deviation of band 1 <= 43.810576: Grass Fields
| Standard deviation of band 1 > 43.810576: Forest Trees

Decision tree inserted into node *ROI*:

Brightness <= 277.747126: Shadow
Brightness > 277.747126
| Mean pixel value of band 4/band3<= 1.890621
| | Mean pixel value of band 4/band3 <= 1.324161: Urban Areas
| | Mean pixel value of band 4/band3 > 1.324161
| | | Mean pixel value of band 3/band1 <= 1.06859: Urban Areas
| | | Mean pixel value of band 3/band1 > 1.06859: Bare Soil
| Mean pixel value of band 4/band 3 > 1.890621: Vegetated Areas

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Figure 3. Decision trees inducted using the C4.5 algorithm.

One of the advantages of decision trees is that they are "white boxes" and can be understood simply as a rule or as a selection of segments structure. So, the description of a class (in this case the rule for hypothesis discarding and spatial conflict solution) is comprised of every splitting of the tree, which is a simple selection over one feature, hierarchically structured.

However, the BU rule in node *ROI* still has to solve the spatial conflicts between class *Rocky Outcrop* and the other classes, since this class was not extracted through segmentation and decision tree classification. The way we did that was to give weights to the classes establishing an order of priority between classes in the case of a spatial conflict. One should notice that between classes *Vegetated Areas*, *Urban Areas*, *Bare Soil* and *Shadow* there could not be any spatial conflicts, since decision trees always split the data into two mutually excluding parts.

The following descending order of class priority was defined: *Urban Areas*, *Bare Soil*, *Vegetation*, *Rocky Outcrop* and *Shadow*. So, for instance, an eventual spatial conflict between classes *Urban Area* and *Rocky Outcrop* would imply in the discarding of the hypothesis of class *Rocky Outcrop*.

Still on the BU rule inserted into node *ROI* we defined re-classification rules based on contextual (i.e. topological) features. After the selection of hypotheses given by the decision tree and the definition of the priority weight for every class, the command *Spatial Resolve* was inserted. This command only solves all spatial conflicts and ends that part of the rule. It is only after the insertion of this command that re-classification rules are to be inserted. As these rules, as well as the segmentation parameters, are universal, i.e. equally applied for every area and every date, they are very simple and only correct obvious misclassifications.

Two reclassification rules were inserted. The first rule is that all *Bare Soil* areas with relative border to class *Urban Area* higher than 0.4 are reclassified as *Urban Area* and the second rule is that all *Urban Areas* with relative border to class *Rocky Outcrop*

higher than 0.3 are reclassified as *Rocky Outcrop*. At this point an important remark should be made: before reclassifying hypotheses through these contextual rules, we merged adjacent segments of the same class; otherwise, as the segments are small and as one real-world object is made in most cases of more than one segment, the reclassification rules would not have the desired effect.

This very same automatic interpretation model can be formatted in another way as well. As in the near future the algorithm C4.5 will be available in the TD step of the InterIMAGE system, it is possible to run the segmentation procedure (using the TerraAIDA Baatz&Shäpe Segmentation operator) in the node *ROI* and still on the TD rule of this node run the C4.5 for the classification of *Vegetated Areas*, *Urban Areas*, *Bare Soil* and *Shadow*. Then the command Global Merge should be selected at the *ROI* node's TD rule. This means all children nodes of *ROI* will receive one single mask, which can or cannot be continuous. The nodes *Urban Areas*, *Bare Soil* and *Shadow* would have the *Dummy Top-Down* operator, which only passes down these masks, and node *Vegetated Areas* would segment the images once more and run the C4.5 algorithm for the classification of *Forest Trees* and *Grass Fields*. Here, as well, the *Global Merge* command should be selected. Finally, nodes *Forest Trees* and *Grass Fields* receive the *Dummy Top-Down* operator.

In the BU step of this hypothetic model, the node *Vegetated Area* would only validate the hypothesis of *Forest Trees* and *Grass Fields* into instances. Optionally the command *Merge Connected* could be inserted and then reclassification rules could be defined. Then, in the BU rule of node *ROI* the *Merge Connected* command would be applied for all of its sun-classes following the priority weights and then the *Spatial Resolve* command after which would come the reclassification rules.

This hypothetic model would generate the very same results as the one we did test. Nevertheless, it would be computationally less expensive. Indeed the InterIMAGE system allows the user to elaborate complex interpretation rules and in more than one way.

4. RESULTS AND FUTURE WORK

As the PIMAR Project is mostly concerned with rainforest suppression, independently of the structure of the vegetation being suppressed, classes *Forest Trees* and *Grass Fields* were merged into a single class named, as in the semantic net, *Vegetated Areas*. The same was done with the reference map produced by the photo-interpreters. Both classifications, i.e. the manually made and the automatically made, were then compared pixel by pixel. Figure 4 shows both classifications and Table 3 shows the confusion matrix calculated from this comparison. Commonly used global and per-class accuracy indexes were computed from the confusion matrix, such as Global Accuracy and Kappa Index, for a global evaluation of the automatic classification, and User and Producer's accuracies (Congalton and Green, 1999).

Looking at fig. 4 it is noticeable that, generally speaking, the classifications look alike. Most of the vegetated areas and urban areas coincide in the two maps. On the other hand, classes *Shadow* and *Rocky Outcrop* were poorly classified. The strategy of slicing a slope image in order to extract rocky outcrops did not achieved the desired effect. A lot of the urban areas in this site have a slope higher than 45^0 and there are few rocky

outcrop patches that have slopes lower than 45^0. Since rock outcrops have similar spectral characteristics as urban areas, some areas of that class were wrongly classified as urban areas. As for the class *Shadow*, the photo-interpreters did not considered shaded areas inside the rainforest as objects of this class. The system does not take it into account when classifying segments, therefore class *Shadow* was over-classified in relation to the reference map. We could have inserted a reclassification rule for turning into *Vegetated Areas Shadow* objects with area smaller than a certain threshold. However this was not done.

There is another difference of class concept between the two classifications: the photo-interpreters classified bare soil areas as urban areas when the bare soil patch is located inside the city, whether they were actually soccer fields or unpaved streets. Even though we have considered this when defining the reclassification rules in node *ROI*, the producer and specially the user accuracies obtained by this class are very poor. Nevertheless, despite the above considerations the results were evaluated as satisfactory for a first test. The Kappa Index of 0.6 and the Global Accuracy of 80% corroborate our judgment.
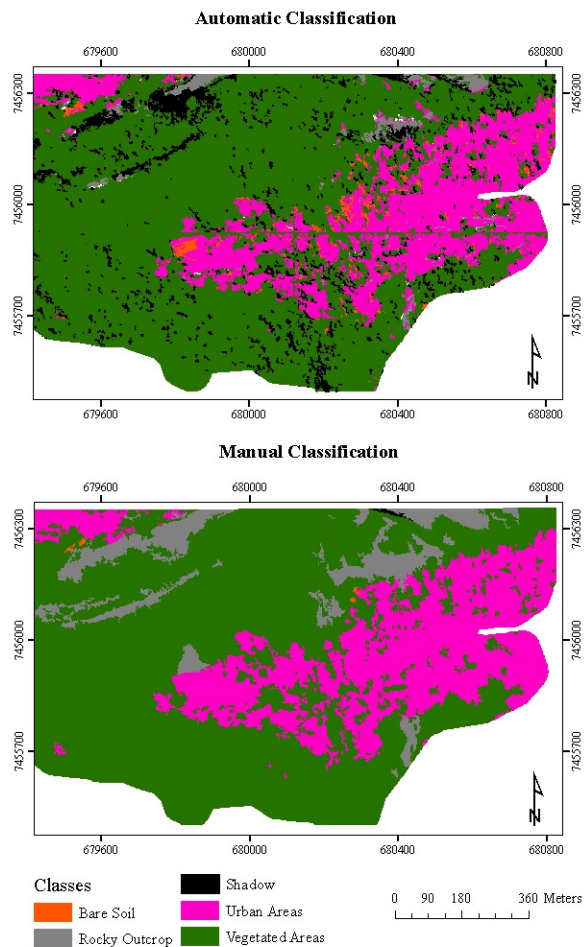

Figure 4. Automatic and manual classifications.

The two most important classes for the PIMAR Project's goals are *Urban Areas* and *Vegetated Areas*. Both classes obtained fairly good user and producer's accuracies, as shown on Table 3. The user's accuracy of 0.91 means that few commission errors are being committed and that when we read *Vegetated Area* on the automatic classification there is a good chance it is

	Rocky Outcrop	Bare Soil	Vegetated Areas	Shadow	Urban Areas	Total
Rocky Outcrop	**15144**	1	1089	3	2989	**19226**
Bare Soil	129	**360**	1723	0	9750	**11962**
Vegetated Areas	29795	198	**591607**	109	34454	**656163**
Shadow	25661	13	63780	**600**	12867	**102921**
Urban Areas	6787	269	12253	0	**205374**	**224683**
Total	77516	841	670452	712	265434	1014955
User´s Accuracy	**0.79**	**0.03**	**0.90**	**0.01**	**0.91**	
Producer´s Accuracy	**0.20**	**0.43**	**0.88**	**0.84**	**0.77**	
Global Accuracy	**0.81**					
Kappa Index	**0.61**					

Table 3. Confusion matrix computed from the pixel-by-pixel comparison between the manual and the automatic classifications.

in fact, or accordingly to the photo-interpreters map, an area of vegetation. We decided that it is better if the classification model is pessimist, that meaning that the model has to be "sure" that a certain area is vegetation to classifying it as such. At the same time, the classification suspects that vegetation suppression has occurred on areas of tough or subjective interpretation. This consideration is of great importance since the final automatic interpretation model will be applied for the next years of analysis and further on as an operational analysis tool. Ideally, we should reduce the commission errors to zero, meaning that the correctors of the automatically made map would only check the not-vegetation areas and validate or not the occurrence of vegetation suppression, considering the precedent year. A heuristic for reducing the commission errors of the automatic classification by editing the thresholds of the decision tree is being conceived and will be reported on future papers. This study shows the results obtained in the testing phase of the automatic interpretation model, which has been carried out over the image of the first year of analysis of the project (2008). In the next phase of our tests, the model will be applied to the image of the year 2009 and only in the area classified as vegetation on the reference land cover map of year 2008, created by the photo-interpreters. A considerable reduction of their work is expected, since they will only be required to check the areas not automatically classified as *Vegetated Area* by the model.

5. SUMMARY AND CONCLUSIONS

The PIMAR Project is currently evaluating the accuracy obtained by an automatic classification model developed and tested with the InterIMAGE object-based image classification system. Such model is being elaborated considering that an user would have only to collect samples of every land cover class through a user friendly interface to obtain, after running the model, the desired land cover map. In this study we present the results obtained with a classification model that uses the C4.5 algorithm, commonly used spectral features and a simple semantic net. The visual analysis and the global and per-class accuracy indexes suggest that the automatically made classification is satisfactorily accurate and has potential for significantly reduce the photo-interpreters work.

In future work we intend to elaborate a way for editing the thresholds of the decision tree in order to reduce ideally to zero commission errors. A less computationally expensive

formatting of the model will be implemented when the C4.5 algorithm is available as a *Top-Down operator* of InterIMAGE.

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