OBJECT ORIENTED ANALYSIS AND SEMANTIC NETWORK FOR HIGH RESOLUTION IMAGE CLASSIFICATION

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Abstract: This work presents a high resolution image classification based on object oriented. The objects are derived by means of multiresolution segmentation. It allows a creation of different levels of segments supporting a hierarchy structure, generating spatial relations between objects and sub-objects. This hierarchy is the bedding for the semantic network. The knowledge is the basis of the semantic. The classification is based on fuzzy rules by the means of descriptors such as: form, texture and relations between objects and sub-objects. Different approaches of classification are assessed: semantic network, selective and context change classification. The tested site is an agricultural area in the city of Nova Esperança-Pr, wherein intended to map the riparian vegetation along of River Porecatú.

Keywords: remote sensing, object oriented classification, segmentation.

1. INTRODUCTION

Remote sensing has made enormous progress over the last decades and a variety of sensors now deliver medium and high resolution data on an operational basis. Nevertheless, a vast majority of applications still rely on basic image processing concepts developed in the early seventies, classification of single pixels in a multi-dimensional feature space. The spatial context plays a modest role in pixel-based analysis. Consequently, classical algorithms of pixel based image analysis are becoming less important for high resolution classification. Although the techniques are well-developed and sophisticated variations such as Bayesian classifier, uncertainty decision rule and multi-criteria evaluation, do not make use of spatial concepts. Concerning to high resolution images special neighboring pixels are highly correlated and it is likely that they belong to the same land cover class.

Alternatives to a pixel based classification are being currently developed for instance the object oriented approach that takes into account the form, textures and spectral information. Object-based classification starts with the crucial initial step of grouping neighboring pixels into meaningful areas, especially for the end-user. This means that the segmentation and object (topology) generation must be set according to the resolution and the scale of the expected objects.

This article deals with the classification of different vegetation types in the riparian environment that can not be separated by the means of spectral information only. Hence, the inclusion of texture and spatial information in the classification schema based on semantic representation of the image is tested and evaluated.

The main objective is to identify riparian areas that occur next to the banks of stream and include both the area dominated by continuous high moisture content and the adjacent upland vegetation that exerts an influence on it. Streamside vegetation protects water quality and provides a "green zone" of vegetation that stabilizes stream banks, regulates stream temperatures, and provides a continual source of woody debris to the stream channel. The riparian management zone has been enforced by local lows. An accurate vegetation map provides guidance on management strategies for preservation the forest along the river.

2 - STUDY AREA

The study area in Figure 1 is located in the North of the State of Paraná (South Brazil), municipality of Nova Esperança and involves an area of 2,380 hectares. This area has been undertaking for sustainable forest preservation. Most of the original riparian environment was exploited along the last three decades for agricultural activities. A Governmental Project called "Paraná 12 meses" intends to map the entire remaining riparian environment for land management. The available data for that study was an Ikonos multispectral image, four bands, and topographic map besides an extensive field data collection.

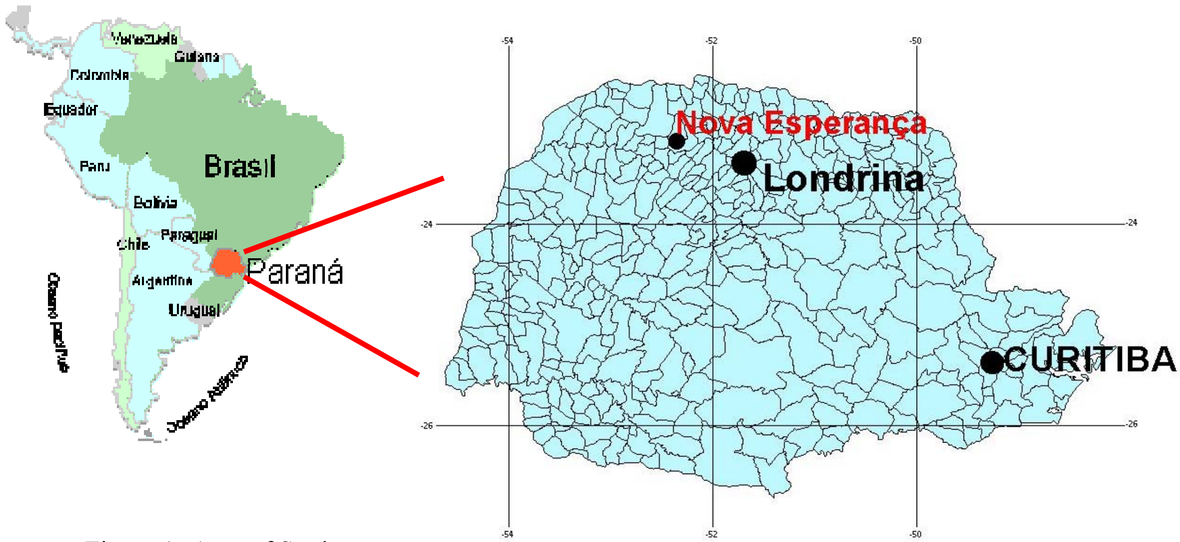


Figure 1- Area of Study

3 - METODOLOGY

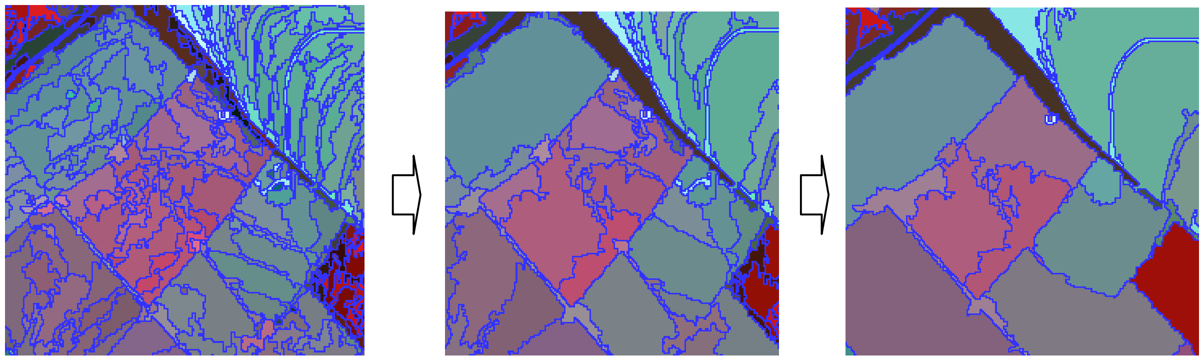
3.1 Segmentation

Semantic information necessary to interpret an image is not represented in single pixels but in meaningful image objects and their mutual relations. The use of semantic information in classification is an important goal for the thematic accuracy.

Since the image consists of pixels the first step in the object oriented approach is group adjacent pixels by the means of region growing technique. It starts with one pixel shaping one image object or region the merge continues until an user specified criteria is reached. The merge decision is based on local homogeneity criteria. The algorithm guarantees a regular spatial distribution of treated image objects. The underlying patented algorithm is essentially a heuristic optimization procedure, which minimizes the average heterogeneity of image objects for a given resolution over the whole scene. Heterogeneity itself is based not only on the standard deviation of image objects but also on their shape. Weighting between spectral and shape heterogeneity enables an adjusting of segmentation results to the considered application (WILLHAUCK et al, 2000, BAAATZ & SCHÄPE, 2000)

The stop criterion for the region-merging process is given by the parameter „scale" and can be edited by the user. It determines the maximum allowed overall heterogeneity of the segments. The larger the scale parameters for one data set, the larger are the image objects. For a given scale parameter, the size of the resulting objects depends on the data characteristics and the map objective. Since the scale parameter can be modified a set of different segmented images can be obtained. The objects generated in a coarser segmentation will inherit the information of smaller objects produced in finer scale parameter segmentation.

This creates a hierarchical network of image objects. Each image object knows its super-object and its sub-objects. That allows the introduction of context into classification process. In this application three different level approach were used to enable the description of super and sub- objects relationships. The relations between the objects can be described by edges or links forming the semantic net. Besides, a concrete representation of the objects relations can be achieved (KUNZ, 1999). Therefore, the feature space have to be extended to spectral as well as non spectral features, which can contribute to an improved distinction between the defined object classes. Thus, geometrical and structural features are taken into account. Figure 2 shows the different degrees of generalization in the images A, B and C. The relationships of the objects depend on the user knowledge, besides the form of the objects can provide hints of image interpretation. Form and color enable the associative perception of the objects and its likely class.



(A)- 10 (B)- 60 (C)- 90

Figure 2- Image segmentation using three different scale parameters

Another important aspect of understanding the content of an image is context. There are two types of contextual information: environmental, which describes the situation of the image (basically time, sensor and location) and local context, which describes the relationships of objects to each other within a certain area of the image – usually neighborhood relationships. In order to model spatial context it is necessary to link them different sized image objects hierarchically and to represent their (semantic) scale relationships. From a classification point of view now the objects non-intrinsic properties such as neighborhood relationships or being a sub-object or super-object are describable. Figure 3 shows the semantic structure based on hierarchical relation between the different segmentation level.

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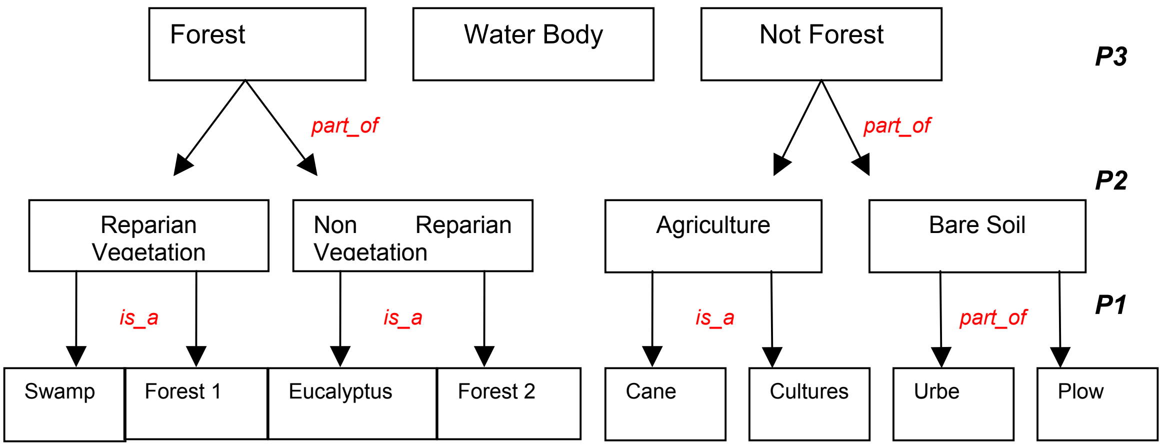


Figure 3- Semantic net based on prior knowledge and image interpretation. P3, P2,P1 are the segmentation level.

Figure 3 shows a concept net with spatial relations. The spatial relations are realized as attributes relations among the objects base on knowledge. The specialization of an image objects is described by the *is_a*. This link type introduces the concept of inheritance. The link *part_of* indicates the object sub-division.

3.2- Classification

In this case, the classification was based on fuzzy logic. Each class of a classification scheme contains a class description. Each class description consists of a set of fuzzy expressions allowing the evaluation of specific features and their logical operation. The control knowledge is represented explicitly by a set of rules. Each rule is composed of a condition and an action part. The condition is formulated by the means of parameters or class descriptors

The formulation of the rules for classification based on segmentation is carried out by the context information and the classes' relationships. A hierarchical network is topologically definite, i.e. the border of a super object is consistent with the borders of its sub objects. .

The classes were described using spectral and shape information. Table 1 shows the list of used parameters. Generally in higher hierarchy spectral information could yield good results, such as mean, brightness and ratio. To distinguish different objects which are very close spectrally form parameters such density, asymmetry and shape index could be useful.The features concerning to texture are based on sub object analysis. The texture features might be related to spectral information or spatial information of the sub objects.

Parameters used in Fuzzy Functions

Mean: $\mu_b = 1/n\sum_{i=1}^{n} c_{l_i}$ *μ_b is the layer mean c_{li} all layers **n** number of pixels.*

Brightness: $br = 1/n_b\sum_{i=1}^{n_b} c_i$ *;Sum of mean values of the layers containing the spectral information divides by their quantity computed for an image object .*

Ratio: $r_b = \mu_b / \sum_{i=1}^{n_b} c_i$ *; ratio of layer **b** is the layer mean μ_b, divided by the spectral sum of all spectral layer mean values* $\sum_{i=1}^{n_b} c_i$.

Shape Index: $\gamma_o = l/4\sqrt{A}$ *; It's the border length **l** of the image objet divided by four times square root of the area.;*

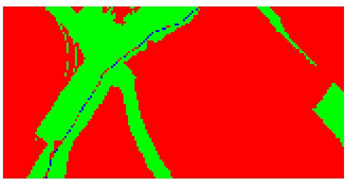
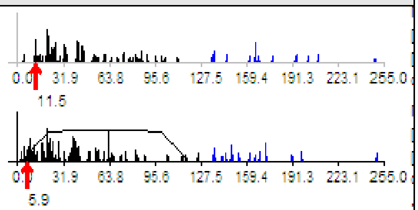
Texture $\sigma = \sqrt{\sum (X_\lambda - \mu)^2 / n-1}$, where X $_\lambda$ = gray level layer $_\lambda$, μ= mean of sub-objects, n number of sub-objects

Table 1- Class Descriptors

A fuzzy rule can have one single condition or can consist of a combination of several conditions, which have to be fulfilled for an object to be assigned to a class. In case of vegetation classification the spectral information of the infrared channel has played and important role. In other hand parameters such shape index and asymmetry can be used to discriminate objects, which differ in shape.

The strategy for the classification was multi-resolution segmentation, which uses information provided by small object primitives to label large scale objects (scale parameters: 10, 60, 90). The selection of scale parameters was purely empiric. The primitive objects in 10 scale, generates bigger objects in 60 scale, and so on.

The classification was based on specialization (Figure 4), that means, starts with bigger objects (the first segmented image) few classes can be depicted, i.e. *forest* and *non forest*, these classes could be divided in sub-classes in the smaller segments, i.e., *swamp* and *eucalyptus*, according to the semantic net. The purpose is to deliver basic information for the classification of level 3 **,** to level 2 and finally to level one (smaller objects) **.**The process of sub-divide parent classes in child sub-classes might take on account supplementary data such as river, lake and roads. The existence of the class *swamp vegetation* depends on existence of river (Figure 4). All the objects are liked within a semantic network that is automatically derived from multi-resolution segmentation. The links between objects and among the layers can be used to formulate the class decision rule.

<table>
<tr><th>Classes</th><th>Image</th><th>Fuzzy Rule</th></tr>
<tr><td>Vegetation
Not Vegetation</td><td></td><td>

Vegetation Not Vegetation
Spectral parameters</td></tr>
<tr><td>Riparian
Not Riparian
Super Class: Vegetation</td><td></td><td>Existence of class River</td></tr>
</table>

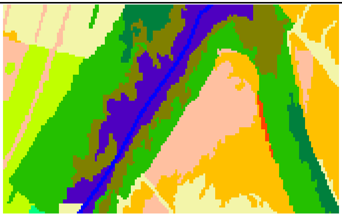
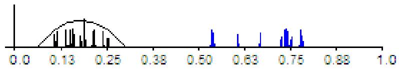
Swamp **Vegetation** *Super Class: Riparian*		 Swamp Forest 1 *Spectral parameters*

Figure 4- Classification base different hierarchical level. Specialization process..

4- CLASSIFICATION RESULTS AND ACCURACY ASSESSMENT

The classification result was compared to another classification based on Bayesian Theory. Some classes such as *swamp vegetation* and *agriculture* had a spectral overlap. Those classes without context information could no be depicted. A detailed comparison of the accuracy assessment using *Tau* is given in Table 2. The contextual classification had a higher consistency especially the classification of *swamp vegetation (varzea)* and *agriculture*. This can be explained with hierarchy classification whereas the relationships between classes were taken into account. The spectral information was not enough to distinguish some classes, hence, objects categorization depends on the relation between objects and sub objects. Figure 5 shows the object oriented classification result Ikonos image. The accuracy of this map was significantly better than Bayesian statistical approach.

Classes	Assessment	
	Contextual	Bayesian
Swamp Vegetation	*0.786*	*0.453*
Agriculture	*0.778*	*0.456*
Eucalyptus	*0.710*	*0.634*
Riparian vegetation	*0.754*	*0.560*

Table 1- Tau's Coefficient of Accuracy

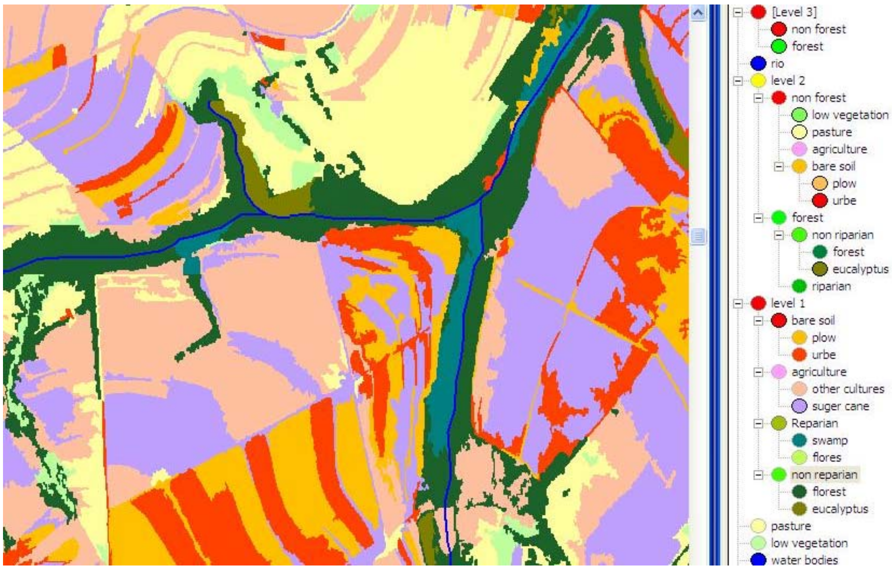


Figure 5- Object oriented classification image.

5 CONCLUSIONS

Regarding the complex and different structures of vegetation, *riparian forest*, *eucalyptus* and *swamps*, multi-resolution segmentation is well suited to generate image objects and to build up spatial relations. In addition contextual information can be used to enhance a classification in terms of applying semantic knowledge to analyses an image. In the present example *swamp vegetation* could be distinguish of moisture bared soil by the means of the context.

First experiences with an extended feature base and a special segmentation process confirm the efficiency of the concept by leading to a better separability of object classes. For a larger knowledge base in the step of semantic classification, more suitable features were desirable and should be found. More features could help in the decision process to obtain a more accurate result. The determination of good valuation functions for spectral as well as non-spectral features in the decision process in the semantic network might be a complex and time consuming task. The structure of the semantic net is still simple, but can be extended in an easy way by adding new concepts and links.

Experience from currently applications demonstrates that segmentation-based classification is in many instances superior to traditional per-pixel methods mainly on high resolution images .

Finally, it might be stated that the presented method and implementations are representing an important progress because it is obvious that a multisensoral analysis is needed to realize the full potential of remotely sensed data. Furthermore for vegetation types detection, the context and semantic rules a fundamental to overcome the constrains of conventional classification methods.

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