GEOAIDA Applied to SPOT Satellite Image Interpretation

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***Abstract*— This paper investigates the application of a knowledge-based approach, founded on semantic networks, to the automatic land use mapping assisted by low resolution satellite images. Alike the visual photo-interpretation, the automatic image interpretation considers scene and sensors knowledge, delivered by an expert photo-interpreter, as well as additional information about the region like the digital elevation model, the position of the emergent rocks, the mapping of the water bodies and the road-network. By this means, the analysis of a scene can be automatically performed, mimicking the reasoning of the photo-interpreter. The implementation of such proposal employed the GEOAIDA [1] system, a flexible environment for image interpretation developed at the University of Hanover, which exploits semantic networks to structure the domain specific knowledge. In the reported experiments, a multispectral SPOT 3 XS image was analysed resulting in a land use map. The automatically obtained results were evaluated and compared with a manually made reference map of the investigated scene. The experimental results demonstrate the potential of a knowledge-based approach for low resolution satellite images interpretation.**

I. INTRODUCTION

The interaction between the environment and the agricultural and industrial activities was a key issue in the agenda 21, a document signed during the United Nations conference on environment and development in Rio de Janeiro [2] and consolidated during the United Nations Conference on Environment and Sustainable Development in Johannesburg [3]. It defined the concept of sustainable development as the most important paradigm to the societies of the new millennium.

In order to improve the rational utilisation of natural resources, it brings the necessity of environmental planning and monitoring. The government agents are faced with uncertainty how to evaluate the drawbacks of bio-renewable resources exploitation.

The technology of remote sensing plays a key role towards this aim. It provides tools to monitor the environmental degradation process and the effects of preservationist measures. Namely, by comparing remotely sensed images of an area at different times during the year it is possible to detect changes on the land cover and to locate the spots where a degradation process started.

Indeed, there are many tools that incorporate the most recent advances in remote sensing. However, despite the fact that there are powerful software packages commercially available, which can be used as monitoring tools for environmental conditions all over the earth, these packages have some characteristics that hinder the full exploitation of this technology: these programs are designed for users with a solid background on remote sensing and or digital image processing.

Thus, often there are not enough people with the required skill to operate the available remote sensing software for monitoring large areas with the minimal periodicity to effectively follow the environmental processes. This is the central question addressed by a cooperation project named ECOWATCH involving German and Brazilian research groups.

The project targets on setting up systems for the automatic interpretation of multi-temporal remotely sensed images that can be used by people, like the technicians of municipalities and government agencies, who do not have specific knowledge about the underlying techniques. The proposed approach presupposes that knowledge-based approaches can in the future automatise the interpretation of satellite images. This is the case of the approach used within the ECOWATCH project.

Although the most part of the information in satellite images is the spectral response measured in several bands, the combination of a knowledge based approach and low resolution satellite images for an automated image interpretation promises some improvements if compared with conventional satellite image interpretation.

In low spatial resolution satellite images, similar to the ones used in this work, it is impossible to perform a structural image analysis, namely, finding the parts of man made objects like houses and buildings. In addition, in such images, distinct land cover classes may present similar spectral appearances what turns more difficult their discrimination. Nonetheless, it does not represent a problem to experienced human photo-interpreters who take advantage of supplementary information (e.g. size, shape and texture) as well as their knowledge background in order to solve contradictory interpretations. Considering that explicitly modeling the experience of a photo-interpreter about a specific site into a knowledge-basis his reasoning can be computationally reproduced, the proposed paper formalises the knowledge of a photo-interpreter through the use of semantic networks. The implementation of such a proposal employs the GEOAIDA [1] system, a flexible environment for image interpretation, which exploits semantic networks to structure the domain specific knowledge. The GEOAIDA approach was successfully applied in the interpretation of high resolution aerial images [4].

Actually few experiments have been reported about the use of knowledge based approaches for low resolution satellite images. The first approach for interpretation of satellite images by use of semantic networks is done by [5]. The analysis of Landsat TM images is done with use of the system ERNEST [6] and a semantic network is derived from a digital topographic database of the examined scene. Besides the spectral response features like compactness, mean curvature, texture standard deviation and texture homogeneity are also measured on satellite images. The image interpretation system ERNEST was designed for general tasks in pattern recognition, the analysis is modeled as a search tree problem with a rule based control.

[7] implements a land cover analysis for a sequence of satellite images of different satellites with use of a temporal model. The investigated scene corresponds to a rural area and the analysis of the images uses special agricultural knowledge as *a priori* knowledge about the scene.

In [8] only the urban areas of satellite images are investigated. The approach of merging images of different satellites is used to improve the detection of urban housing development.

The present paper reports experiments performed with GEOAIDA for the interpretation of satellite images. It is organised this way: Section II presents an overview of GEOAIDA; section III describes the experiments performed in this work, whose results are analysed in section IV. The text ends with a discussion about the next steps within this research.

II. GEOAIDA

Semantic networks consist of nodes and links, and are defined as directional acyclic graphs. Specifically, in the GEOAIDA system, nodes represent the objects expected in the scene, whilst links describe the relations between the objects. In this context, the initial description of the scene contents, including nodes and links, is called conceptual semantic network. GEOAIDA defines three different sorts of nodes, *generalisation*, *compound* and *end*. The generalisation nodes are used to split up and branch into alternative scene interpretations. The compound nodes represent objects which require the recognition of others in lower hierarchical level, belonged to the compound node. Final nodes, which do not have offsprings, are just linked to their respective parent that may be a compound or generalisation node.

On the contrary to what occurs in other knowledge based remote sense image interpretation systems based on semantic networks like ERNEST [9], [10] and AIDA [11], GEOAIDA does not put any functionality into the links, which are merely bi-directional relations between two nodes. The links reveal to each node only its parent and its offsprings Thus, each node knows its ”genealogy”, contains information about the object which it represents, and encloses attributes and methods dynamically administrated.

The sequence of interpretation can be split up in two complementary processes, called *top-down* and *bottom-up*. In the top-down process, hypothesis, represented as hypothesis instance nodes, are generated from the possible occurrence of any expected object, see in figure 1. Each one of the hypotheses corresponds to some concept of the conceptual network. The bottom-up approach tries to validate the hypothesis. When a hypothesis is validated it turns into an instance of a predefined concept, in the counter case the hypothesis is discarded. Such validation occurs in cases where the values of the parameters of the instance and its components are between predefined ranges. These ranges are in general modeled by fuzzy sets. In this way, the interpretation process generates the symbolic description of a proposed scene.

III. EXPERIMENTS

A. Data set

The proposed approach was applied to a test area in the State of Rio de Janeiro, the municipality county of Teresópolis, with an area of $850km^2$, which is placed in a mountainous region in southeast of Brazil .

A SPOT 3 XS image acquired on April 7, 1996 with a spatial resolution of $20m$ per pixel was used in the experiments. For this test, a false color composition of the bands 1-3 (channel R band 3, channel G band 1 and channel B band 2) was available. A cut of the examined region is shown in figure 2.

In order to assess the performance of the proposed approach, a reliable land cover / land use map was employed as reference. It was produced by visual photo-interpretation and validation by extensive field work. This map was produced by the same experienced photo-interpreters that yielded the knowledge about the scene modeled in the proposed approach.

Additional input data for the automatic image interpretation system GEOAIDA is the digital elevation model (DEM), the positioning of emergent rocks, the mapping of the water bodies and the road-network. The major reason to consider the additional data is the differentiation of distinct classes with similar spectral responses. However, the utilisation of the DEM allows taking a supplementary advantage. The severe topography in the region of interest conjugated with the relatively low sun angle at the time of the satellite overpass produced significant shadowing effects in the input image. This phenomenon can be observed in figure 2. Because of this effect, the spectral

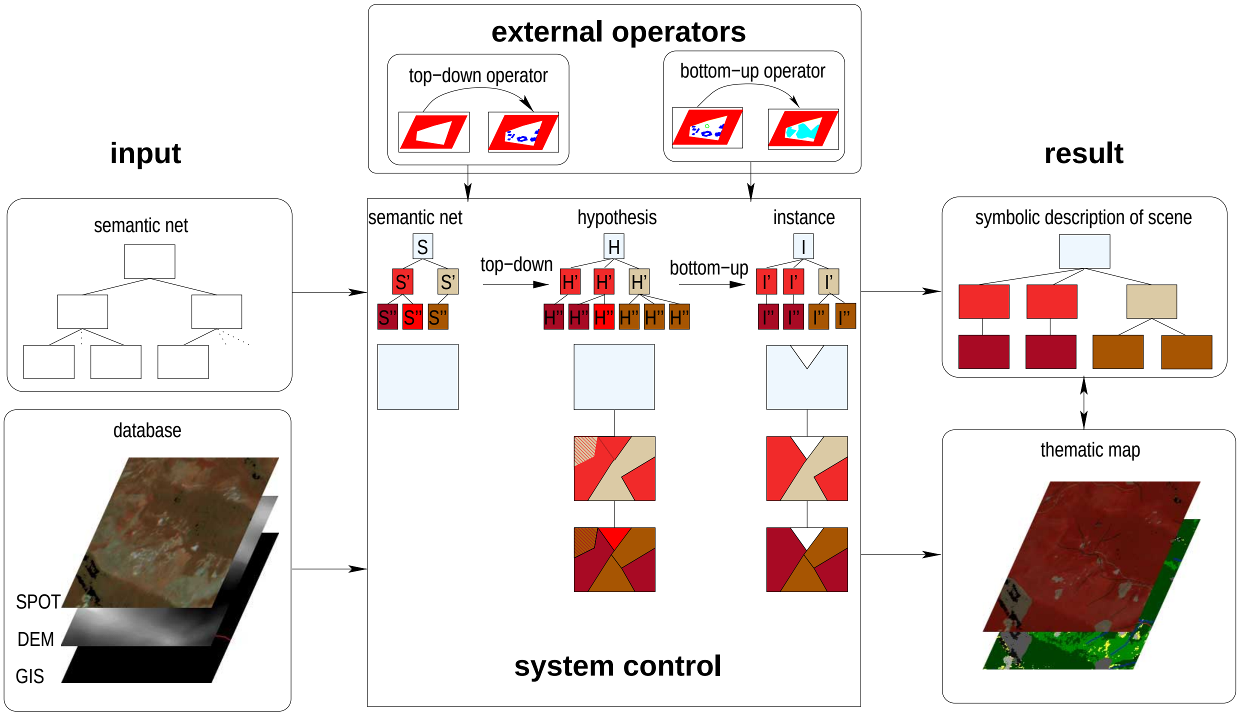

Fig. 1. System Overview GEOAIDA

response of a class may present severe variations, turning its classification more difficult. The literature mentions that the C Correction [12], [13] is adequate for that purpose, yielding quite good results. Following this procedure, the slope effect can be compensated by employing the DEM as well as the sun and sensor positions at the moment of image acquisition. In the present paper, the C correction was implemented in a pre-processing step, before any classification procedure.

In this work, the DEM provides an additional advantage, it allows the distinction between vegetation classes that have nearly the same spectral response, but occur in different altitudes.

The information of existing paved roads and water bodies was not processed in the analysis, but included in the resulting interpretation of the scene to give a better orientation on the result map. The use of rivers and paved roads as hints to improve the interpretation for e.g. existence of urban area was not investigated, but could be an option in future.

B. Procedure

First specific knowledge about the region was acquired by interviewing the photo-interpreters who produced the reference maps. This process aimed at understanding the way that they approached the image analysis, considering both the spectral appearance of the remotely sensed image and other sources of data.

The classes present in the region of interest are: Dense forest, low vegetation, paramos, road, rock, water and urban. The spectral response of the class dense forest in such image is dark red. The classes low vegetation and paramos have the similar spectral responses, light red; however, paramos, which is a kind of natural low density vegetation, occurs only on the top of mountains over about 1100 meters. The class rock, depending on the density of its vegetal coverture, may present different spectral responses; nonetheless, because the location of the rocks is time-invariant it can be included as prior information. As well, the class road, depending on the presence or absence of asphalt, may present distinct spectral responses, but it also can be considered time-invariant, so it can be included as prior knowledge. The class urban possesses a characteristic texture that can be used in its recognition. To end up, the class water can not be perceived in the input image; thus, this information will be copied from the water bodies information about this region.

As a consequence of such information, the classes mentioned hitherto can be grouped in three clusters: *Natural* which encompasses the classes rock, water, dense forest and paramos, while the cluster *rural* only contains the class low vegetation. Besides, the cluster *built-up* comprehends the classes urban and road.

With the expected classes acquired from the photo-interpreters the semantic network in figure 3 was build to model the examined scene and transferred into GEOAIDA.

In order to accomplish the generic model of the scene, operators, both top-down and bottom-up, should be included inside the nodes of the semantic network. Two different sorts of image processing operators are used in the top-down process, one evaluates the spectral response the other classifies the

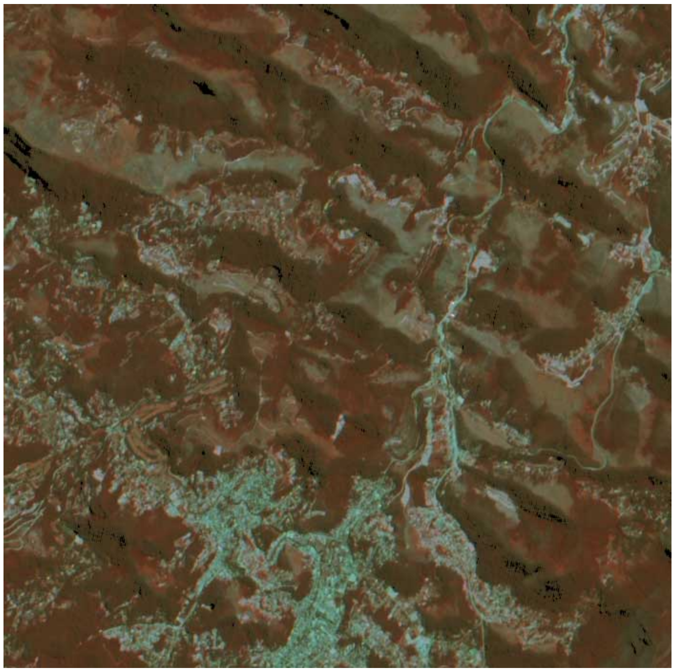

Fig. 2. SPOT 4 XS False Color Composite of Bands 1-3

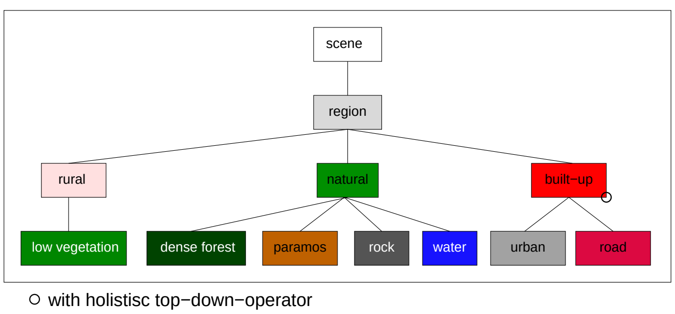

Fig. 3. Implemented Semantic Network

texture in the pixel's neighbourhood. Besides, known objects belonging to time invariable classes, e.g. water bodies and rocks were given to the system, by a copy operator.

In the bottom-up process additional data can be used to discriminate the classes that have similar spectral responses. That is the case of the class pasture and a special vegetation named paramos, a natural grassy high altitude ecosystem, that appears only in higher regions. In the example in figure 2 the class paramos is not existent.

IV. Results

The reference map along with the interpretation result are shown in figure 4. The classes and corresponding colors are also given in the figure.

In order to permit a quantitative analysis of the results, table I presents the classification matrix, comparing the experimental results with a reliable reference map. In table II for each class, the percentage measures of omission and commission errors are calculated.

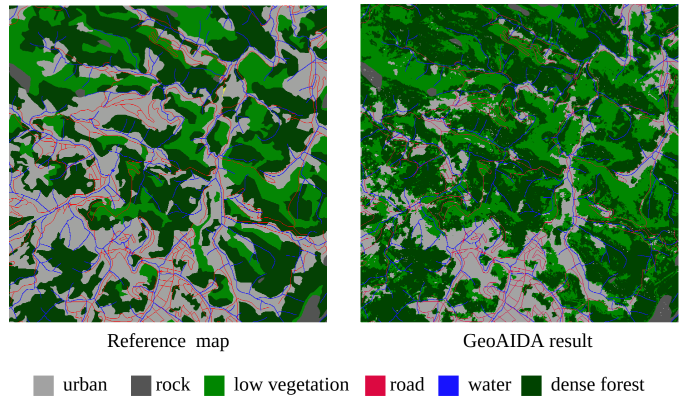

Fig. 4. Interpretation Results

V. Discussion

An interactive procedure composed the manual labour that resulted in the reference map. In a first stage, taking as basis specific knowledge about the remote sensor and the region of interest alongside with additional data about the region, the photo-interpreters carried out the visual interpretation of the SPOT image. Such knowledge has great influence over the human behaviour while performing the image interpretation. The criteria employed in the visual interpretation were gathered, and then were explicitly formalised by means of a knowledge basis given as input to the GeoAIDA system. The outcome of this experiment reproduces this reasoning.

A distinctive detail between the manual and the automatic approaches is that, during the visual interpretation, when the photo-interpreters ran into doubts, these were solved in loco by fieldwork. Besides, such visits to the region of interest provided an additional contribution; they served to evaluate and validate the outcome of the visual interpretation. Therefore, the production of the remarkably reliable reference map involved several visits to the area of interest. Nonetheless, even though no information about that fieldwork had been delivered to the system, the automatic knowledge based approach was capable of producing an overall accuracy of 70.4% while compared with the reference map.

Analysing in detail the result produced by GeoAIDA, it can be observed that the main sources of error are the misclassification of classes urban, low vegetation and forest, see tables I and II. Taking just the class urban into account, the omission error, meaning the pixels of that class wrongly attributed to other classes, was of 52.43%, being 18.49% of the urban areas misclassified as forest and 33.94% as low vegetation. The main reason of this error is the poor detection of low density urban areas which have nearly no texture and present spectral response similar to the classes of vegetation. Consequently, in those cases, considering only the characteristic texture, it is difficult to decide for the right class.

TABLE I

CLASSIFICATION MATRIX

Class	Forest	Rock	Low Veg.	Water	Urban	Road	Total
Forest	161720		19361		32762		213843
Rock		5576					5576
Low Veg.	28121		64698		60153		152972
Water				15924			15924
Urban	2821	52	1534		84315		88722
Road						12963	12963
Total	192662	5628	85593	15924	177230	12963	490000

Column: Pixel Reference Map   Row: Pixel GEOAIDA Result

TABLE II

MISCLASSIFICATION RATES

Class	Omission Error	Commission Error
Forest	16.06%	24.24%
Rock	0.01%	0.00%
Low Vegetation	24.41%	57.71%
Water	0.00%	0.00%
Urban	52.43%	4.97%
Road	0.00%	0.00%

Here additional criteria like density of the road network etc. can be used in order to improve the low density urban areas classification.

Another source of errors is the confusion between low vegetation and forest. Even though, the C correction, a method to compensate the radiometric distortions caused by the cross effect between topography and sun position, had been applied, the result showed a poor classification of the vegetal classes. This fact indicates that the pixel classification unaided may produce an unsatisfactory classification. A potential solution for this problem is the exploitation of additional sources of information, for instance size and altitude of the regions. This will be checked in the sequence of this research.

VI. CONCLUSION AND FUTURE STEPS

This paper investigated the application of a knowledge based approach, established on semantic networks, for the automatic land use mapping of low resolution satellite images. When compared with conventional supervised interpretation methods, the knowledge based strategy presents some benefits. Due to the possibility of considering additional information about the region of interest beyond the pixel intensities, the knowledge based approach takes advantage of the supplementary data to resolve the dubious cases with which conventional methods cannot deal precisely.

The proposed approach employs the knowledge based methodology to mimic the reasoning of the photo-interpreter and thus, performs an automatic analysis of a low resolution satellite image. The implementation of the knowledge based approach demonstrated in the present paper employed the GEOAIDA system, which exploits semantic networks in order to structure the domain specific knowledge.

In GEOAIDA, for the interpretation of different types of object classes, specific image processing operators can be used. Conflicting interpretations for one region can be solved by simple access to external data. In this sort of problem, potential sources of additional data are geographic information systems.

The current stage of development of this research does not completely exploit the features of GEOAIDA that may significantly improve the overall accuracy. Another probable cause of this outcome is the absence, so far, in the knowledge basis of information picked up in loco during fieldwork. Forms of solving such inconsistencies will be investigated in the sequence of this work.

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