IMPACT OF KNOWLEDGE-BASED TECHNIQUES ON THE ANALYSIS OF MEDIUM-RESOLUTION SATELLITE IMAGES OF THE AMAZON

R. Feitosa [a,*], C. Mattos [b], R. O. V. Santos [a], L. F. G. Rego [c], A. A. C. Pereira [d]

[a] PUC - Dept. Electrical Engineering., R. Marquês de São Vicente 225, 22453-900, Rio de Janeiro/RJ, Brazil
(raul, rafael)@ele.puc-rio.br
[b] ATECH Foundation - Innovations Dept., R. do Rocio 313/11, 04552-000, São Paulo/SP, Brazil - cmattos@atech.br
[c] PUC - Dept. Geography and Environment, R. Marquês de São Vicente 225, 22453-900, Rio de Janeiro/RJ, Brazil
regoluiz@rdc.puc-rio.br
[d] ATECH Foundation - SIVAM/SIPAM Dept., Av. Rio Mar 185/3, 69053-180, Manaus/AM, Brazil
augusto@it.atech-mn.br

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ABSTRACT:

This present work evaluates the use of knowledge-based techniques for the analysis of medium-resolution satellite images of the Amazon, and estimates the impact they may bring to the task of mapping the deforestation in this region by. Landsat images of Rondônia State were submitted to a supervised classification; the editing of these classifications, an usually manual process that depends totally on the knowledge and experience of the analyst, was then performed using a knowledge base implemented in eCognition. The results showed that more than 30% of the editing step could be automated using these techniques, increasing the efficiency of the deforestation mapping from Landsat images in the study area.

KURZFASSUNG:

Der vorliegende Artikel berichtet über die Anwendung von wissensbasierten Techniken in der Klassifikation von Satellitenbildern mittlerer Auflösung des Amazonas Gebietes. Der Schwerpunkt ist die Einschätzung, in wie weit das System SIPAM (System für den Schutz des Amazonas Gebietes) durch solche Techniken Abholzung auf Bildern mittlerer Auflösung automatisch feststellen kann. Landsat Bilder des brasilianischen Bundesstaates Rondônia wurden für eine überwachte Klassifikation verwendet. Die üblicherweise manuelle Nachbearbeitung der konventionellen spektralischen Klassifikation, der starkt von der Erfahrung des Interpreters abhängt, wurde mit Hilfe der eCognition Software modelliert und mit Testbildern überprüft. Es hat sich dabei herausgestellt, dass sich mehr als 30% der Bearbeitungsschritte durch die wissensbasierten Techniken automatisieren liessen, und folglich eine erhebliche Effizienzerhöhung erreicht wurde.

1. INTRODUCTION

In face of its recognized global, regional and local importance, and the threats that jeopardize its long-term existence, the Amazon Region has been the object of interest and concern of many, from politicians to scientists, from environmentalists to the general population. In search of measures that ensure a sustainable development of this region and avoid the deforestations, burnings and environmental impacts that characterize the predatory human occupation process of the Amazon in the past few decades, many programs, policies, institutional and legal instruments have been proposed and implemented. The Brazilian SIVAM/SIPAM Project (System for the Vigilance and Protection of the Amazon) is one of these initiatives. Using modern technologies, advanced data processing and communication systems, and a vast network of ground, orbital and airborne sensors, it monitors the region's ecosystems and human activities, generating data for weather, environmental, law enforcement, logistics, and air traffic control applications. Among SIVAM/SIPAM's many tasks is the monitoring and mapping of deforestation, using Remote Sensing data.

Remote Sensing technologies have allowed the monitoring of vast areas, such as the Amazon, its natural ecosystems, productive lands and urban areas. Besides the increasing number of satellites and sensors, many computer systems have been generated, incorporating the latest advances in Remote Sensing. In spite of the progresses observed in the latest years, the image processing is still a predominantly manual process that requires a great effort and expertise from the analyst.

Recently, the interest for Knowledge-Based Systems that model in a computer environment the knowledge of the analyst, and try to emulate his ability to combine data from different sources and formats, and to use them for image analysis, has increased (Bückner et al., 2001; Clément et al., 1993; Liedtke, 1997; Matsuyama and Hwang, 1990; McKeown et al., 1985; Niemann et al., 1990). Such systems reproduce the analyst's reasoning, in order to automate part of the task that in the conventional systems is performed entirely by the human operator.

* Corresponding author.

The number of such solutions applied to medium spatial resolution satellite images (e.g., Landsat) has been limited (Kunz, 1999; Kunz et al., 1997; Largouët & Cordier, 2000; Suzuki et al., 2001; Zhang, 1998). For the Amazon Region, in particular, very little has been done.
The main objective of this work is to estimate the impact of knowledge-based techniques on the analysis of medium-resolution satellite images of the Amazon, for mapping the region's deforestation, by estimating how much of the manual steps of the Landsat images processing can be automated.
SIVAM/SIPAM's usual image processing is based on supervised classification of Landsat images, comprising the following main steps: a) selection of training sample polygons, b) use of a statistical classifier (e.g., maximum likelihood), c) manual editing of the results.
The step b) is automatic, but the other two are manual. This work refers to the automation of (at least part of) the step c), by modeling the analyst's reasoning during the edition of the classified image. The result of this automation will not eliminate, but reduce the manual editing effort performed by the analyst, thus increasing the productivity of the whole process.
The results and conclusions of this work shall support the decision to incorporate knowledge-based technology into new image processing software packages for monitoring the Amazon.
A portion of a Landsat image of Rondônia State, in the Brazilian Amazon, was selected as study area for this experiment.
The following sections of this document describe: the knowledge base generated for the study area (Sec. 2), the experimental evaluation procedure (Sec. 3), the obtained results (Sec. 4), and the main conclusions of the work (Sec. 5).

2. KNOWLEDGE BASE

The knowledge base for this project was built in cooperation with an experienced photo-interpreter, familiar with the SIPAM Project and with the Amazon deforestation theme. Starting from an initial report on the interpretation protocols, the knowledge base and its constituent rules were defined, trough successive cycles of interviews and refinements, until the final version.
For the sake of simplicity, in the following paragraphs the terms *supervised*, *edited* and *final* refer, respectively, to *supervised classification*, *manually edited classification* and *knowledge-based classification*. The manually edited classification provided by the human expert, was used for comparison with the proposed automatic knowledge-based method.

2.1 Input Data and Legend

The designed knowledge-based system has the following inputs:

- The image to be classified;
- The supervised classification, including the classes *Agriculture*, *Forest*, *Regeneration*, *Shadow* and *Water*;
- *Urban Areas* location mask;
- *Rivers* location mask (approximated)*.

The classes identified in the final classification are: *Agriculture, Urban Area, Cloud, Forest, Regeneration, Shadow* and *Water*.
It is important to notice that the initial supervised classification does not encompass the classes *Urban Area* and *Cloud*, present in the edited and final classifications. Actually, the pixels from those classes are assigned to *Agriculture* in the supervised procedure. This fact merely reflects an approach chosen by the photo-interpreter, who differentiates the three classes only during the manual edition stage (post-supervised classification stage).

2.2 Knowledge Base Simplified Description

Natural language descriptions of the final classes used in this project are shown here in a simplified way, grouped by the three most remarkable confusions between classes (Table 1). The task of the photo-interpreter - and thus the task of the designed knowledge-based system - is to resolve (or to reduce as much as possible) these confusions.
The first noticed confusion comprises the *Agriculture*, *Urban Area* and *Cloud* classes. While big clouds have bright white cores, allowing for a relatively simple spectral classification, small clouds and cloud borders have the same observed color as agricultural areas.
The second detected confusion is between *Forest* and *Regeneration* classes. These two classes are different types of vegetation covers, and are distinguished by brightness or texture parameters.
The last reported confusion happens between *Shadow* and *Water*, classes characterized by low spectral values in all bands.

Final Class		Class Descriptions
1	*Agriculture*	Defined as *Agriculture* in the supervised classification. It is nor *Cloud* nor *Urban Area*.
	Urban Area	Defined in IBGE's geopolitical maps.
	Cloud	Defined as *Agriculture* in the supervised classification and with high brightness – "cloud core"; Defined as small *Agriculture* areas, bordering objects of high brightness - "cloud border"; Defined as small *Agriculture* areas, projecting *Shadows* in a specific direction and orientation – "small clouds".
2	*Forest*	Defined as *Forest* in the supervised classification and with low brightness.
	Regeneration	Defined as *Regeneration* in the supervised classification; Defined as *Forest* in the supervised classification and with high brightness.
3	*Shadow*	Defined as a dark object with a *Cloud* object nearby, in a specific direction and orientation.
	Water	Defined as a dark object near the river locations (hydrographic mask); Defined as a dark object with no associated *Cloud* object.

Table 1. Simplified description of the rules constituting the knowledge-based system

* Data on both urban areas and rivers were obtained from topographic maps of the Brazilian Institute of Geography and Statistics (IBGE), at the 1:250.000 scale.

3. EXPERIMENT DESIGN

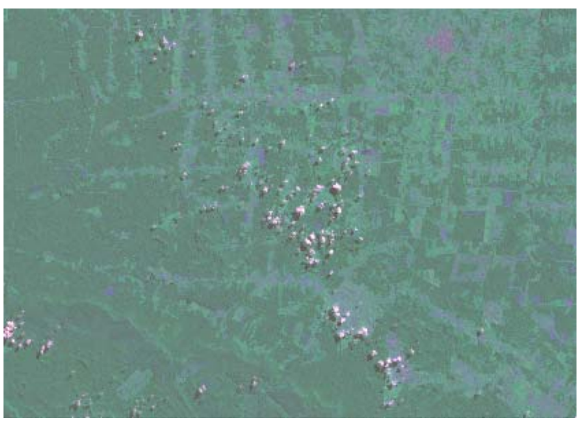
A prototype was built using eCognition, which modeled the knowledge base given before. The basis for this evaluation was a Landsat image of the Rondônia State, in the Brazilian Amazon (scene 231/066), from 2002, bands 3, 4 and 5, in UTM projection. A segment containing 2098 rows and 1485 columns was selected, in the tiff format, in which all classes are represented. Figure 1 shows the selected segment with a composition of bands 3, 4 and 5 in the RGB channels.

A pixel classifier was used for the supervised classification. Segments with less than 16 pixels were eliminated and assigned to the class of the majority of their neighbors.

Geopolitical maps from IBGE indicating the urban areas, as well as the hydrographic network were used as auxiliary data.

The first step was the segmentation, using a homogeneity criteria exclusively related to the spectral response. The segmentation was performed in such a way to ensure that no segment had more than one class assigned to it by the supervised classification. All knowledge-based interpretation procedure considered each segment as an object, characterized by its mean spectral response, area, and its position in relation to the other objects in the image.

Figure 2 (a) shows the result of the supervised classification. The result of the manual edition is shown in Figure 2 (b).



(a)

Figure 1. Image segment used in the experiment*

4. RESULTS

The results of the knowledge model are shown in Figure 2 (c), and in Tables 2 and 3 in the form of confusion matrices respectively for the supervised classification and for the final knowledge-based classification, in both cases in relation to the edited classification used as reference. The values in these Tables are given in number of pixels.

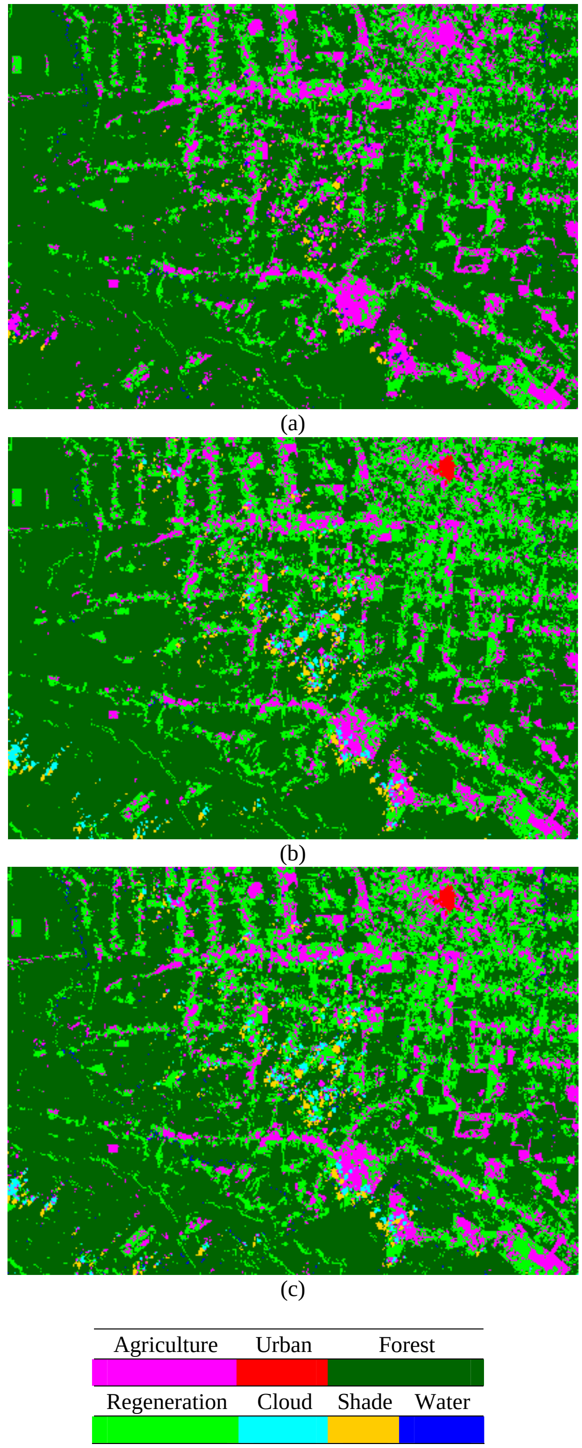


Figure 2. Result of the supervised classification (a); result of the edited classification (b); result of the final knowledge-based classification (c)**

* Full image available at http://www.ele.puc-rio.br/~raul/ATECH/Segmento_de_teste.tif.

** Full images available at http://www.ele.puc-rio.br/~raul/ATECH/Supervisionada.tif (a), http://www.ele.puc-rio.br/~raul/ATECH/Editada.tif (b), and http://www.ele.puc-rio.br/~raul/ATECH/Final_Corrigida.tif (c).

Super-vised	Edited						
	A	U	C	F	R	S	W
A	268269	5189	27502	13056	49807	252	68
U	0	0	0	0	0	0	0
C	0	0	0	0	0	0	0
F	833	0	177	2056160	125595	20466	127
R	11316	3	254	25794	490144	29	22
S	0	0	0	3	0	11541	47
W	909	9	169	3006	237	2842	1704

Table 2. Confusion matrix relating the supervised classification with the edited classification. A (agriculture), U (urban), C (cloud), F (forest), R (regeneration), S (shade), W (water)

Final	Edited						
	A	U	C	F	R	S	W
A	261823	0	4440	11897	49305	133	57
U	0	5201	0	0	0	0	0
C	6336	0	23057	1138	312	74	11
F	354	0	109	1977044	14763	2550	40
R	11872	0	324	97516	601143	44	26
S	702	0	172	3049	35	29774	76
W	240	0	0	7375	225	2555	1758

Table 3. Confusion matrix relating the final classification with the edited classification. A (agriculture), U (urban), C (cloud), F (forest), R (regeneration), S (shade), W (water)

The three main confusion groups mentioned in Section 2.2 are clearly visible in Table 3, involving the classes:

- *Agriculture* × *Urban* × *Cloud*,
- *Forest* × *Regeneration*,
- *Shade* × *Water*.

The following paragraphs analyze the performance of the prototype in terms of its ability to resolve each one of these main confusion groups.

4.1 Agriculture × Urban × Cloud

As mentioned before, the supervised classification does not contain the classes *Urban* and *Cloud*, which appear as *Agriculture* in the supervised classification. As a consequence, the omission error for *Agriculture* is very low in the supervised classification. The confusion matrices show a recognition performance for *Agriculture* in the supervised classification higher than in the final classification (268269 to 261823). The side effect of this practice is the low recognition performance for the classes *Urban* and *Cloud*, which were in fact ignored in the supervised classification.

The performance of the final classification is more equally balanced among these three classes than in the supervised classification. Most of the *Cloud* pixels, and all *Urban* pixels are recognized, although with a small reduction in the recognition (around 2%) for *Agriculture*.

A simple computation indicates that the omission error for the classes *Agriculture*, *Urban* and *Cloud* changed from 5%, 100% and 100% in the supervised classification to 7%, 0% and 18% in the final classification, what represents an important improvement.

It is worth mentioning that the knowledge-based approach had nearly no influence on the number of *Agriculture* pixels erroneously labeled as *Regeneration*. Actually, in the interview with the photo-interpreter, no rule was mentioned which could bring about such a change (see Table 1).

4.2 Forest × Regeneration

Tables 2 and 3 clearly show the difficulty to separate the classes *Forest* and *Regeneration*. Again, the behavior of the prototype must be analyzed for these two classes together. The final classification recognizes little less pixels of the class *Forest* than does the supervised classification. On the other hand, there is a remarkable improvement in the recognition performance for the class *Regeneration*. The use of knowledge changed the omission error from 2% and 26% to 6% and 10% for these respective classes.

It is important to introduce at this point a remark, which applies particularly but not only to these two classes. The photo-interpreter compared discrepancies between the final and the edited classifications, and for many regions considered the knowledge-based outcome more accurate than the edited one. A more careful edition would probably imply in better performance figures for the knowledge-based method than those shown in Tables 2 and 3.

A further comparison of the final and edited classification indicated that most discrepancies occur on pixels at the borders between one class and the other. In fact, around 87% of the total area assigned to *Regeneration* in the edited classification and to *Forest* in the final classification form thin one-pixel wide branches. For pixels labeled as *Forest* in the edited classification and as *Regeneration* in the final classification this percentage is equal to 37%.

4.3 Shade × Water

The confusion between *Shade* and *Water* is quite common in satellite image classification, since both classes have a dark appearance. It was in the discrimination between these classes that the prototype made the most extensive and successful use of the knowledge-based techniques.

The confusion matrices show that most pixels erroneously assigned to *Forest* in the supervised classification were corrected to *Shade* in the final classification. This was done in two steps. Initially, the dark pixels were assigned to an auxiliary class named *Dark_Body_0*. Almost all dark pixels labeled as *Forest* in the supervised classification moved thus to this new class *Dark_Body_0*. In the next step, these dark pixels were separated between *Shade* and *Water*, by exploring specific knowledge. Basically, the dark pixels near *River* were recognized as *Water*. This information was available in hydrographic maps, which due to their low resolution provide only an approximate location of the rivers in the image. A fuzzy rule was formulated that takes into account the distance of the object to be classified to the position of the nearest river in the map.

To recognize a dark pixel as *Shade*, the knowledge-based method looks for a *Cloud* at a given distance and at a given direction that could project shadow over that dark body.

The confusion matrices show that this procedure was able to efficiently separate these two classes and consequently improve the recognition performance (values on the diagonal) not only for *Shade* but also for *Water*.

4.4 Global Evaluation

The experiments performed so far do not allow estimating directly the reduction of the edition time achieved by the use of the knowledge approach. Nonetheless, it is possible to estimate the proportion of the area misclassified in the supervised approach and in the knowledge-based approach. These figures are shown in Table 4.

Approach	Agriculture/ Urban/Cloud	Forest/ Regeneration	Shade/ Water
Supervised	46361	217498	23853
Knowledge-Based	24549	185615	5566

Table 4. Number of misclassified pixels by the supervised classification and by the knowledge-based method

The difference between the second and the third row in the Table, gives the proportion of the edition work done automatically by the prototype. The knowledge-based method was able to do 47% of the edition work for the group *Agriculture/Urban/Cloud*. For the group of classes *Shade/Water* it managed to automatically correct 75% of the misclassified pixels. For the classes *Forest* and *Regeneration*, the method corrected 15% of the misclassified pixels. The knowledge method did automatically, in average, across these three groups, 45% of the edition work.
For this particular image the prototype performed around 33% of the edition automatically in terms of area.
The knowledge base built in this experiment did not take the relative class occurrence into consideration. If the areas of the image covered by each class were different, the performance could be quite distinct as well. The group of classes for which the method brought the least improvement was the most frequent one. It is possible to estimate the performance in a situation where the image area was equally distributed among all classes. It corresponds to normalizing the confusion matrices, by dividing the column values by the sum of the corresponding columns.
Table 5 shows the percentage of pixels that would require correction after the supervised classification and after the final knowledge-based classification. The last column on the right contains the average value across the table rows. It indicates that under this hypothesis, the knowledge-based classification would do around 80% of the edition work.

Approach	A	U	C	F	R	S	W	Average
Supervised	5	100	100	2	26	67	13	45
Knowledge-Based	7	0	18	6	10	15	11	9

Table 5. Percentage of misclassified pixels by the supervised classification and by the knowledge-based method.
A (agriculture), U (urban), C (cloud), F (forest),
R (regeneration), S (shade), W (water)

4.5 Generalization

Some aspects limit the generalization of the results and the conclusions obtained in this experiment. They are:

- The performance is clearly dependent on the proportion of the image area covered by each class;
- The accuracy of the reference data relies entirely on the experience of the photo-interpreter; no ground truth was available for performance validation;
- Just one image was used in the evaluation;
- The knowledge-based approach was just preliminarily explored in the experiment; the knowledge base can still be substantially enriched with potentially positive impacts on performance.

Particularly promising is the use of multi-temporal knowledge, which is in fact explored by the photo-interpreter, but was not modeled in this experiment due to lack of data.
A definitive evaluation of the potential of this technology to automate the edition procedure will require a more accurate work on building a knowledge base that represents more truthfully the reasoning of the photo-interpreter, as well as a more extensive experimental validation. This is precisely the most important and expensive task of the development of a knowledge based interpretation system. A key purpose of this work was to collect evidences to justify such an investment. In this sense, the results achieved so far are encouraging and reinforce the worldwide tendency of increasingly using knowledge-based methods to build automatic remotely sensed image interpretation systems.

5. CONCLUSION

This paper presents an evaluation of the so-called knowledge based techniques as tools to automate the interpretation procedures of Landsat images of the Amazon. The experimental results showed that the method was able to correct automatically around 1/3 of the errors produced by a conventional supervised classification. Around 1/3 of the erroneously classified pixels were automatically corrected by modeling the reasoning applied by the photo-interpreter in the edition phase.
An even better performance can be expected by improving the knowledge base. Particularly promising is the use of multi-temporal reasoning, which uses information of images and classification results from previous dates.
Although limited by the number of images used in the experiment, as well as by the reduced time available to build the knowledge base, the results obtained so far encourage the use of this approach for the development of new more automatic remotely sensed image interpretation tools.

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