## **Remote Sensing Image Mining Using Ontologies**

Marcelino Pereira dos Santos Silva Universidade do Estado do Rio Grande do Norte mpss@dpi.inpe.br

## Abstract

The explosive growth of image databases is overwhelming the current data analysis capacity of remote sensing images. This paper approaches image mining proposing an architecture to help specialists getting high level information from satellite data. Image ontology, data mining and digital image processing are the basis of the proposed architecture for recognizing semantic information in large remote sensing datasets.

*Keywords: image mining, ontology, graph mining.* 

### 1. Introduction

Remote sensing satellites are currently the fastest growing source of geographical information. Satellites such as NASA's Terra and Acqua generate circa 3 Terabytes of imagery daily. The widespread availability of such datasets has led to huge investment in systems for archival of remotely sensed data. For example, Brazil's National Institute for Space Research (INPE) has more than 130 Terabytes of image datasets, covering 30 years of remote sensing activities, which are being organized in a data center for on-line access. Strategic information from these remote sensing images are strongly demanded in many areas, including government (e.g., security and social purposes), economy (e.g., crop forecasting), hydrology (e.g., water resources monitoring), and so on.

However, our capacity to build sophisticated data collecting instruments (such as remote sensing satellites, digital cameras and GPS) is not matched by our means of producing information from these data sources. Currently, most image processing techniques are designed to operate on a single image, and we have few algorithms and techniques for handling multitemporal images. This situation has lead to a "knowledge gap" in the process of deriving information from images and digital maps [19]. This "knowledge gap" has arisen because there are currently few techniques for image mining and information extraction in large image datasets; thus we are failing to exploit our large remote sensing archives.

One key example concerns Amazon deforestation. Brazilian government and society are facing a huge challenge: the preservation of the Amazon tropical forest, which takes more than 50% of Brazil's territory, Gilberto Câmara Instituto Nacional de Pesquisas Espaciais gilberto@dpi.inpe.br

involving seven other frontier countries. In a complex scenario, economic, social and political factors are involved in the deforestation problem, what demands effective decisions and actions to decelerate such process. In order to monitor the extremely fast process of land use change in Amazonia, it is very important that INPE is able to use its huge data archive to the maximum extent possible. In this context, we need to develop new image mining techniques, and this paper proposes an architecture for remote sensing image mining using ontologies, digital image processing, graph mining and pattern matching.

## 2. Review of previous work

#### 2.1 Image segmentation and image mining

In the process of image analysis and information extraction, segmentation algorithms are used to partition the image into regions related to the relevant areas according to the application criteria [4]. A region is defined as a set of continuous pixels, with twodimensional distribution, presenting uniformity related to some attribute. Segmentation algorithms use primarily region growing, edge detection, combination of both [25].

The tools and techniques used for smart analysis of large repositories are the subjects dealt by Knowledge Discovery in Databases (KDD) [9]. Data mining is the KDD step that performs the method selection, which will be used to find patterns in data, followed by the effective search for interesting patterns in a particular representation format and the best adjustment of algorithm parameters for the proposed task. Image mining uses KDD techniques taking into account the complexity of the image domain, which is presented in Figure 1.

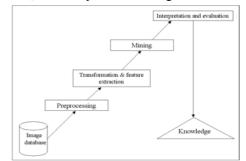


Figure 1: Image mining process [30]

The images of a dataset are selected according to criteria related to the application. In the preprocessing phase, feature extraction techniques are applied to these images. The mining process uses the features extracted to discover relevant patterns. The results are then interpreted to generate results that can be applied in problem understanding, decision making or other activities [30].

Nagao and Matsuyama [21] developed, in Kyoto University, the first high level vision system for aerial image interpretation. The processing modules of the system operate on a common dataset. The analysis process is divided into the following phases: smoothing, detailed segmentation, analysis of areas. and communication among object detection subsystems. GeoMiner [13], developed at Simon Fraser University, is a spatial data mining system prototype able to characterize spatial data using rules, compare, associate, classify and group datasets, analyze patterns and perform data mining in different levels. ADaM [27], a NASA's project with the Alabama University in Huntsville, is a tool set to mine images and scientific data. It performs pattern recognition, image processing, optimization, association rule mining, among other operations.

## 2.2 Image representation using graphs

Graphs are mathematical abstractions extremely useful to solve different problems. A graph consists of a set of vertices and a set of edges (one edge connects two vertices) [22]. Different graph models (e.g., hierarchical, relational, conceptual) add resources to the basic representation, allowing them to be used to represent and manipulate information in many domains: genetics, bioinformatics, images, computer networks, and so on. Once segmented and described, an image has an object representation, which can be mapped to a graph formalism.

Some interesting approaches have used graphs to represent and manipulate images. Petrakis & Faloutsos [24] employed attribute relational graphs (ARG's) to represent the content of medical images, in order to allow similarity searching in image databases (Figure 2). Once stored using ARG's (to represent object properties and relationships) [2], the images could be retrieved through descriptions to express selection criteria that should be satisfied. This way, describing some objects or relationships found in an image of a patient, the users could specify search conditions and retrieve similar images from the database, in order to improve diagnosis and treatment procedures.

Region adjacency graphs (RAG's) are used by Wang et al. [29] to aggregate image regions. This work proposes a segmentation algorithm based on edge detection and region growing and, in order to avoid an extreme segmentation, the regions are mapped to a RAG. Thies [26] performs medical image hierarchical partitioning based on significant regions for human visual perception. The proposal uses segmentation and hierarchical region organization, where each region of lower scale is contained in a region of higher scale. The process generates hierarchical region adjacency graphs (hRAG's) representing each region as a vertex with attributes, and edges describing the topological scale of regions.

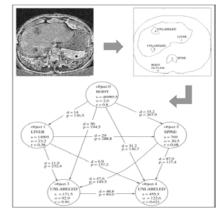


Figure 2: ARGs representing medical images [24]

#### 2.3 Graph mining

Graph mining approaches different techniques to extract information from structural data. The substructure mining searches similar subgraphs in a set of graphs. Discovered substructures are used to compress original data, allowing to summarize detailed structures and to represent structural concepts. An example is shown in Figure 3. Graph clusters may supply a better data understanding, outlining topologies, hierarchies and representing useful knowledge [17]. Inexact graph matching is used to identify instances of substructures, ignoring minor variations and enabling pattern discovery even if noise or small differences are present in data [6, 14]. Anomaly detection in graphs has many applications, including fraud and network intrusion detection [23].

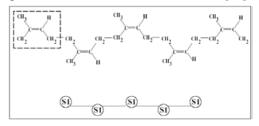


Figure 3: Natural rubber atomic structure [15]

Relational learning concerns the ability of learning recursive hypothesis and restrictions in variables. Graph based systems are competitive in the learning tasks, once they supply a powerful, expressive and flexible representation [12, 16]. Holder [15] approaches pattern discovery in relational datasets represented by graphs based on the Minimum Description Length principle, heuristics that defines the better substructure as the one that minimizes the graph description when it's compressed using this substructure. It's implemented in Subdue [28], which mines substructures and patterns, performs clustering, compression, relational learning, and graph inexact isomorphism.

## **3.** Proposed architecture

## 3.1 Using ontologies for image mining

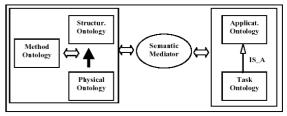
One of the main challenges in current image mining techniques is the incorporation of semantical information into the knowledge discovery process. Most of the image understanding toolkits (such as ADAM [27]) are based on a collection of low-level processing functions, that have to be combined with themselves or third party tools, depending on human capacity of aggregating knowledge to results, once the mining methods use low level functions (e.g., shape recognition and pattern extraction). The challenge in image understanding and image mining is the incorporation of semantic information in this process, in order to make the feature extraction and image mining process less dependent on "ad-hoc" methods that may not be general. We consider that ontologies can be used as a way to insert application specific knowledge in the mining environment. The objective of an image architecture based on ontologies is to bring the image mining process very near to the user application domain.

An ontology describes a particular reality with a specific vocabulary, using a set of hypothesis related to the intentional meaning of the words in this vocabulary [10]. Ontologies can represent the knowledge of a domain through a declarative formalism, allowing the description of objects, their properties and relationships. Câmara et al. [7] discusses the ontology of remotely sensed imagery, proposing a multi-level ontology in order to include semantic information in the image understanding process. The authors consider that remote sensing images are ontological instruments to capture landscape dynamics. Câmara et al. considers that geographical processes occur in a multi-level space, resulting from the interaction of different spatial-temporal phenomena in a physical landscape. The focus of the ontological characterization is the search for changes, instead of the search for content. Instead of considering an image as a separate entity, this view proposes the use of image ontologies to detect spatial-temporal configurations of geographic phenomena.

The proposal takes into account that images has a particular, distinct description independent of the domain ontology a scientist would employ to extract information. The ontology domain for images has three interrelated components (Figure 4):

• *Physical ontology* – describes the physical process of the image creation, focusing the knowledge about the relation between the reflected energy by terrain surface and measures obtained by the satellite sensor.

- *Structural Ontology* contemplates geometric, functional and descriptive structures that can be extracted using techniques for feature extraction, segmentation, classification, and so on.
- *Method Ontology* it's composed of a set of algorithms (that perform transformations from the physical level to the structural level) and data structures that represent reusable knowledge in the form of image processing techniques (filtering, smoothing, and others).



# Figure 4: Ontological context for image information extraction [7]

The relation between the image ontology and the application ontology is reached through a semantic mediator, which performs two basic functions:

- Identify the specific image processing and pattern recognition algorithms (described in the method ontology) that are necessary to extract the desired structures from images, or to transform the physical values (pixels) in order to get the demanded information.
- Map concepts of the domain ontology to extracted structures from the set of images. For example: a domain ontology may contain a concept road; using the semantic mediator it's possible to identify roads in the linear structures that belong to the structural ontology of the image.

## **3.2** Proposed architecture

We propose an architecture for image mining in large remote sensing databases which implements the ontologybased information extraction outlined above. In the first phase of the process, we build a structural ontology for the phenomena to be identified. It's also necessary to build the application ontology for the chosen domain. For example: if the focus is deforestation caused by wood extraction, then selected images of this phenomenon must be submitted to the process of structural ontology building; at the same time, an application ontology must be built describing elements, relationships and hierarchies.

Graph pattern extraction techniques (graph mining) will generate structural signatures of segmented images. Using the image signatures that reflect deforestation and the application ontology of the domain, the semantic mediation (performed by a specialist) generates image ontological patterns (Figure 5).

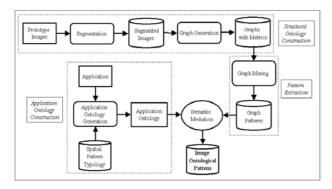


Figure 5: Process of building ontological patterns

In the second phase of the process, it's assumed that iterations with many datasets in the first phase have built a sufficient repository of ontological patterns to analyze datasets of the chosen domain. Then, in this second phase, the image dataset to be mined must be submitted to the structural ontology construction, followed by the graph pattern extraction. Through a pattern matching process [5], the obtained graph patterns (of the second phase) and the ontological patterns repository (of the first phase) are processed to find positive instances able to show spatial configurations in the mined image dataset (Figure 6).

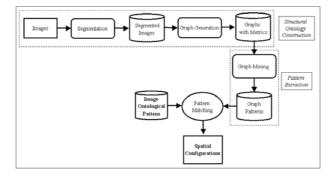


Figure 6: Spatial configuration identification

#### **3.3** Building the structural ontology

In this proposal, the semantic gap between the obtained elements (objects, relationships, and others) and their context meaning (semantics) is filled through ontologies (structural and application), which supply resources to support the remote sensing image complexities.

The structural ontology concerns the geometric, functional and descriptive structures obtained from the images using feature extraction and segmentation. To build this ontology, it's necessary to derive and integrate characteristic components of the image, in order to construct a repository describing the image in a structural manner, specifying properties, relationships, hierarchies.

The construction of the structural ontology may be outlined in the following steps (Figure 7):

Selection of a set of images, according to the phase of the process;

- Segmentation of each image, in order to build a segmented image repository;
- Extraction and storage of graphs and metrics from the objects of the segmented image repository.

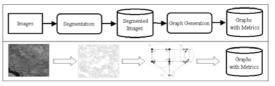


Figure 7: Construction of the structural ontology

## 3.4 Building the application ontology

The application ontology describes the vocabulary related to a particular domain (e.g., ecology), specifying contexts and activities of the real world, their specializations and features, beyond identifying specific classes of elements and respective relationships. The construction of this ontology demands the definition of the application domain, supported by structural models and spatial pattern typologies.

Specific event series that cause deforestation generally have particular features. Deforestation processes caused by different factors (subsistence farming, cattle ranches, agribusiness, wood extraction, and so on) in tropical forests are commonly associated to spatial patterns of deforested areas [8, 11, 20] (e.g., Figure 8).

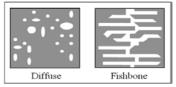


Figure 8: Spatial patterns of tropical deforestation

During the process of ontology construction, the specialist determines the application and its respective tasks [7]. Typologies and spatial pattern structures are then used to format the application ontology, which will contain detailed, contextual and hierarchical information about the modeled domain (Figure 9).

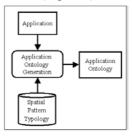


Figure 9: Construction of the application ontology

### 3.5 Graph pattern extraction

The structural ontology, represented by graphs, supplies a rich and computable information repository about images. Graph mining procedures (e.g., substructure mining) must be performed to allow identifying image patterns using this information. Such step makes possible signature identification that characterizes images, extracting spatial information through structural patterns. The results of this step are then stored in a graph pattern repository, to be used as "structural signatures" of their respective images (Figure 10).



Figure 10: Graph pattern extraction

## 3.6 Ontological pattern generation

Once defined the application ontology and obtained the graph patterns, the specialist performs the semantic mediation process, which consists on attributing ontology instances to structural signatures (graph patterns), according to Figure 11. The result of this process is an image ontological pattern repository, which associates each task of the application ontology to one or more graph patterns (signatures), thus overcoming the semantic gap between the object level and image semantic level.

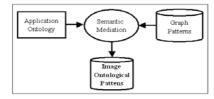


Figure 11: Obtaining ontological patterns

### 3.7 Obtaining spatial configurations

Assuming that the translation of land use and cover patterns to graphs is well succeeded, it implies that pattern matching will be an inexact graph-matching problem [15], that is, locate in a graph (which represents objects of the segmentation process) subgraphs that correspond to desired patterns. An example is the fishbone pattern, which will be transformed in graphs when present in an image. Subgraphs that correspond to fishbone will be associated through an inexact graph matching process to obtain spatial configurations (Figure 12).

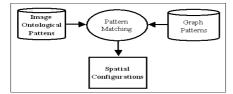


Figure 12: Pattern matching – inexact graphs

#### 3.8 Application domain: Amazon deforestation

Desertification, climate change, biodiversity loss and others can bring hard consequences to the environment and to human being. Causes and consequences of land use and land cover changes (and environmental, social and economics impacts) have motivated researches. Lambin [18] emphasizes that land user change is a global change generator, interacting with climate, ecosystems processes, biochemical cycles, biodiversity and human activities.

The Amazon case is characterized by the complexity and dimension of subjects involved in the land use and land cover changes [3]. Alves [1] brings an investigation about the spatio-temporal dynamics of Amazon deforestation, using remote sensing satellite images for spatial patterns analysis of deforestation in 1970s and between 1991 and 1997. Some information from this work: the deforested area has increased from 10 million hectares in the 1970s to nearly 59 million hectares in 2000; the fast advance of deforestation followed 1970s and 1980s Brazilian government policies.

Once the fast deforestation causes soil degradation, social confrontation and precarious urbanization, the fast and precise identification of areas with such tendencies will increase the chances of preventing and reducing the consequences of the process. Daily, different satellites register data of these contexts, which images are sent to many institutions. Image mining tools can improve the analysis capacity of these huge strategic datasets.

In order to illustrate the image mining process, let's consider the wood extraction example in the Amazon. The application (wood extraction), the aggregated knowledge (e.g., historical, social and environmental characteristics) and spatial pattern typologies related to the domain will be used to build the application ontology for this case. At the same time, selected images that characterize this problem (wood extraction) are segmented, their graphs are generated and stored (structural ontology). At this point, graph mining tasks are performed, which result in signatures (patterns) of the graphs (and their respective images). Then, using the application ontology and the structural ontology (graph patterns/signatures), it's possible for the specialist to build image ontological patterns (semantic mediation), associating instances of the application ontology to generated signatures (Figure 13).

In the next phase of the process, a procedure to detect areas with accelerated or irregular deforestation caused by corporative wood extraction can be performed. In this second phase, a set of candidate images is selected and segmented, which graphs are generated and mined. The obtained signatures are then submitted to a pattern matching process with the signatures of the application ontology (1.1.1.1 e 1.1.1.3). The selected instances in the pattern matching process will indicate images where the characterized wood extraction may occur. In the example of the Figure 14, the images H, I, J, K, L, M are characterized by the image mining process using ontologies, indicating accelerated or irregular deforestation caused by corporative wood extraction.

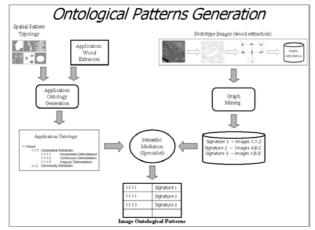


Figure 13: First phase of the image mining process

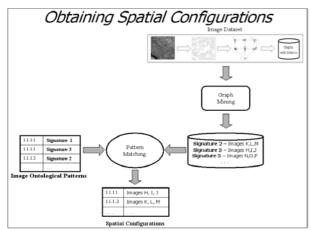


Figure 14: Second phase of the image mining process

## 4. Conclusions

This paper proposed an architecture for remote sensing image mining using ontologies, digital image processing, graph mining and pattern matching. The process is performed in a two-phase procedure. Plentiful image datasets may be used to detect and prevent the Amazon deforestation, the application domain of this proposal.

The Amazon case is characterized by the complexity and dimension of subjects involved in the deforestation problem. The structural process and its history are well known and researched by INPE. Moreover, the institution has a rich remote sensing image database, which supplies a wide spatio-temporal coverage of the Amazon territory.

Transforming objects into semantic entities remains a relevant scientific challenge not yet solved. Furthermore, the proposal involves resources and techniques of different areas, becoming the technology development and integration another significant challenge. INPE's experience in image processing, analysis and software development supplies relevant evidences to guide methodological and computational procedures.

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