What's In An Image?

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Abstract. This paper discusses the ontological status of remote sensing images, from a GIScience perspective. We argue that images have a dual nature—they are fields at the measurement level and fiat objects at the classification level—and that images have an ontological description of their own, distinct and independent from the domain ontology a domain scientist uses. This paper proposes a multi-level ontology for images, combining both *field* and *object* approaches and distinguishing between image and user ontologies. The framework developed contributes to the design of a new generation of integrated GISs, since two key benefits are achieved: (1) the support for *multiple perspectives for the same image* and (2) an emphasis on using images for the detection of *spatial-temporal configurations* of *geographic phenomena*.

Keywords. GIScience, remote sensing images, ontology of geographic data, integrated GIS.

1 Introduction

Remotely sensed imagery is one of the most pervasive sources of spatial data currently available to researchers who are interested in large-scale geographic phenomena. The variety of spatial and spectral resolutions for remote sensing images is large, ranging from IKONOS 1-meter panchromatic images to the polarimetric radar images soon to be part of the next generation of RADARSAT and JERS satellites. Recent advances in remote sensing technology, with the deployment of a new generation of sensors, have improved considerably such application areas as environmental monitoring and urban management.

Despite over 30 years of experience in data gathering, processing and analysis and the now ubiquitous nature of remote sensing imagery, the ontological status of images remains an open issue. It is surprisingly difficult to provide a straightforward answer to a very basic question, “What’s in an image?” or to put the same question differently, “What is the ontological status of the information content of remote sensing imagery?” This paper examines answers to this question, from a GIScience perspective.

The motivation for this paper is two-fold: First, in order to grow into a full-fledged scientific discipline, GIScience [1] will have to develop a sound conceptual basis for all of the different types of computer representations of geographic space including images, vector data, locational information, and digital terrain models. Second, understanding the ontological status of remote sensing imagery is germane to the design of GIS technology that can integrate images seamlessly into a spatial database environment. Integration is particularly relevant in the context of a new generation of spatial information systems that is expected to provide support for capturing, representing, and using ontologies [2].

The remainder of this paper is organized as follows. Section 2 gives a brief introduction to the use of ontologies for spatial data, followed by an examination of field vs. object properties of images (Section 3). Section 4 formulates the requirements for an ontology of images, followed by a multi-level ontological perspective for a more complete description of the information content in images (Section 5). Section 6 presents a representational framework for future implementations of this multi-level ontology. Section 7 concludes with the consequences of our findings for the design of integrated GIS.

2 Ontologies and Spatial Data Types

The most widely accepted conceptual data model for spatial information considers that the geographic reality is represented as either fully definable entities (*objects)* or continuous spatial variation (*fields)* [3]. The *object model* represents the world as a surface occupied by discrete objects, with a geometric representation and descriptive attributes. The *field model* views the geographic reality as a set of spatial distributions over geographic space. Although this simple dichotomy has been subject to criticism [4], it has proven to be a useful frame of reference and has been adopted, with some variations, in the design of the current generation of GIS technology [5].

The field-object dichotomy is a very generic concept [6], with no support for specific semantics of the different types of spatial data. This problem has led many researchers to consider the use of ontologies as a means of knowledge sharing amongst different user communities thereby improving interoperability among different geographic databases [7] [2].

Ontologies are content theories, which contain a general set of facts to be shared, and whose main contribution is to identify specific classes of objects and relations that exist in some domain. Thus, informally defined, ontologies are agreements about shared conceptualizations. A formal definition would be that ontology is a (possibly incomplete) axiomatization of the possible models of a logical language [8]. Representation of user domain ontologies, in this context, is considered an essential part of capturing the specialist's conception of the information space [9].

The investigation of the ontological status of spatial data types is a major ongoing research effort in the GIScience community [10] [11]. Fonseca and Egenhofer [2] introduced the concept of Ontology-Driven Geographic Information Systems (ODGIS) to support users of geographic information to achieve an agreement on the basic entities of the geographic world. Smith and Mark [7] also argue that these models of the geographic world will converge on each other and that a formal description of those entities would create an ontology of geographic kinds. ODGIS is a framework in which ontologies from different user communities can be combined, leading to the integration of different sources of geographic information.

Researchers and GIS practitioners are increasingly recognizing the importance of ontologies as a practical means of knowledge sharing. A recent example is the land-cover classification scheme of the Food and Agriculture Organization of the United Nations (FAO/UN), which is intended as a common vocabulary to be used by the remote sensing community [12]. This scheme defines a large number of different land cover types (with a strong emphasis on vegetation types), which could be identified in remote sensing images. Given the importance of monitoring changes on land use and land cover worldwide, the FAO proposal is a major step towards knowledge and information sharing in the remote sensing domain.

3 Fields or Objects?

The application of the concepts of ontologies of spatial types to the characterization of images has not been extensively studied in the literature. Câmara *et al.* [13] consider images to be a subset of digital terrain models (DTMs) and, therefore, subclasses of *fields*. In this view, an image is a 2-dimensional function, arising from the sampled response of a region of the Earth to an external energy source (the sun or a radar beam) as measured by a passive or active sensor, respectively. Since a number of geometric algorithms can be applied to DTMs as well as images (e.g., filtering, enhancement, differentiation, or warping), this view has a large practical usefulness. The simplicity of the raster representation has certainly helped in the development of a large theory of image processing algorithms, based purely on the geometric properties of images [14, 15].

However, the conception of images as a strict specialization of fields is inadequate for capturing the full nature of their informational content. There is a fundamental difference between *digital terrain models* and *images* as representations of continuous phenomena. Most DTMs are derived from either field surveys organized for hypothesis testing (as in the case of ecological studies) or from standardized data collection missions (as in aerial photogrammetry). The process of measurement is directly linked to an ontological commitment made by the researcher *a priori*, where the collected values should capture the phenomena under study (e.g., samples of the oxygen content in a lake).

By contrast, in remote sensing, the properties of each sensor (i.e., the number of bands as well as the spectral, temporal, and spatial resolutions) are the results of a compromise between the needs of various research communities and the availability of sensor technology. The continuous variation of the spectral response of the land cover, which is the specific phenomena captured by the pixel values, often misses what a domain scientist considers as relevant. These measurements are merely components of the more complex information content of an image. Most image classification techniques do not rely explicitly on the conversion between digital counts and the actual energy captured by the sensor, but they use the digital counts to extract features. As a consequence, viewing images as fields of values of reflected energy is insufficient for their ontological characterization.

The limitations of the field perspective to the ontology of images have led some researchers to view a remotely sensed image as a container of an implicit set of objects, which are extracted by manual or semi-automated analysis procedures. Following the terminology used by Smith and Mark [7], this view proposes that the spatial analysis procedures creates *fiat objects*, which correspond to objects that exist only in virtue of demarcations effected cognitively by human beings, as opposed to *bona fide objects*, whose boundaries exist independently of human cognitive acts.

The object perspective is taken by Bittner and Winter [16], who view the image as a set of individual objects that can be identified by means of manual or automated interpretation procedures. They make the important distinction between fiat objects created by spatial analysis and objects in the world to which these fiat objects are supposed to correspond. A spatial analysis fiat object owes its existence to (1) the notion of a corresponding object in the world, (2) an act of measurement (in this case, the remote sensing process), and (3) a creative human act of spatial analysis. This perspective is motivated by a number of situations, most notably in the case of high-resolution images.

Although the object perspective captures a fundamental component of the ontology of images and forms a basis for a large set of image classification techniques, it is still incomplete. In many cases, there is no corresponding object in the world, since we deal with purely physical phenomena. Figure 1 shows a set of Normalized Difference Vegetation Index (NDVI) images derived from the AVHRR sensor of the NOAA-12 satellite. These images are snapshots of the temporal evolution of the land cover over South America, related to the seasonal variations of the vegetation. NDVI images present the variation of a continuous variable, shown in Figure 1 as a color presentation where ranges of the variable are assigned to different colors. Since the image is not composed of fiat objects, the concept of corresponding objects in the world is not useful to convey the ontological contents of the image. As a result, NDVI images are better modeled as a continuous field that evolves over time.

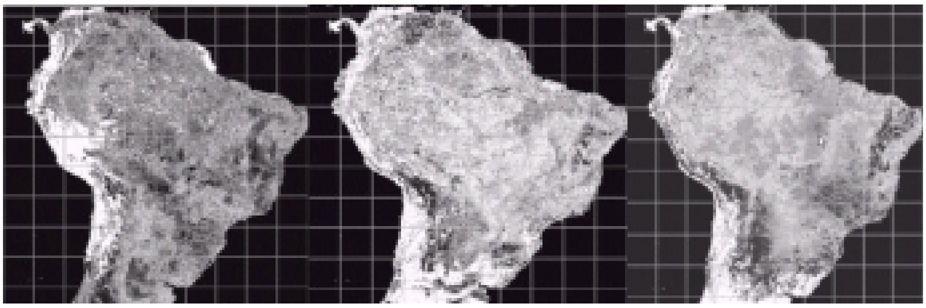

Figure 1: Normalized Vegetation Index Images derived from AVHRR sensor (NOAA-12 satellite) for South America. Left January 2000, center May 2000, and right June 2000 (source: CPTEC/INPE).

4 Requirements for an Ontology of Images

The preceding discussion has outlined why it is impossible to give a simple answer to the question "What's in an image?" We have examined two distinct (and complementary) approaches to the ontological description of remotely sensed imagery and argued that neither is sufficient by itself to support the full process of knowledge representation for image data. The underlying reason is that images have a dual nature: Images are fields at the measurement level, but fiat objects at the classification level. It is, therefore, possible to talk about *the image paradox*: while the domain scientist may believe she recognizes objects in a remotely sensed image, she is actually measuring fields. To account for this dual use, a more complete understanding of the role of images as sources of geographic information is needed.

We propose that remotely sensed images are ontologically *instruments for capturing landscape dynamics*. This approach considers that geographic processes occur in a multi-scale space and result from the temporal and spatial interactions of different spatial phenomena over a physical *landscape*. This view leads to the following requirements for an ontology of images:

- **Intrinsic properties**: Remotely sensed imagery cannot be reduced to the case of a single-date, single-band raster geometry, since most real-world uses of remotely sensed data rely on their temporal and multispectral nature. Image ontologies should consider their intrinsic properties: *periodical data acquisition, multispectral capability*, and *spectral resolution.*
- **Non-specific, periodical data capture:** Unlike most field surveys associated with DTMs, where measurement is strongly linked to the phenomenon under study, images are general-purpose data capture devices. Within the limits of their intrinsic properties, they capture responses from different types of objects and geographic phenomena.

- **Focus on trajectories of change**: A geographic landscape is an ever-changing scenario, and the process of data capture by remote sensing satellites implies that an image is a measurement that captures snapshots of change trajectories. Therefore, the focus of the ontological characterization of images should be on the *search for changes* instead of the *search for content*. The emphasis of such ontologies should not be placed on simple *object matching and identification* procedures, but on capturing *dynamics* over a finite *landscape*.
- **Reuse of algorithmic knowledge**: There is a significant amount of reusable knowledge for different applications in the form of image processing algorithms, such as principal components, maximum-likelihood classifier, and texture measures.
- **Dependence on measurement**: Image content is strongly dependent on the measurement process. This observation is particularly important when comparing data acquired by different sensors. Figure 2 shows an area in the Brazilian Amazon forest obtained by LANDSAT TM (optical) and RADARSAT L-band (radar). In the LANDSAT image it is possible to claim the existence of world objects (e.g., forest, as well as deforested and regrowth areas), whereas in the radar image is it more appropriate to consider the existence of land cover patterns, which result in different textures in the image. In fact, a large number of radar image classification algorithms are texture-based relying on the detection of statistical and structural texture measures.

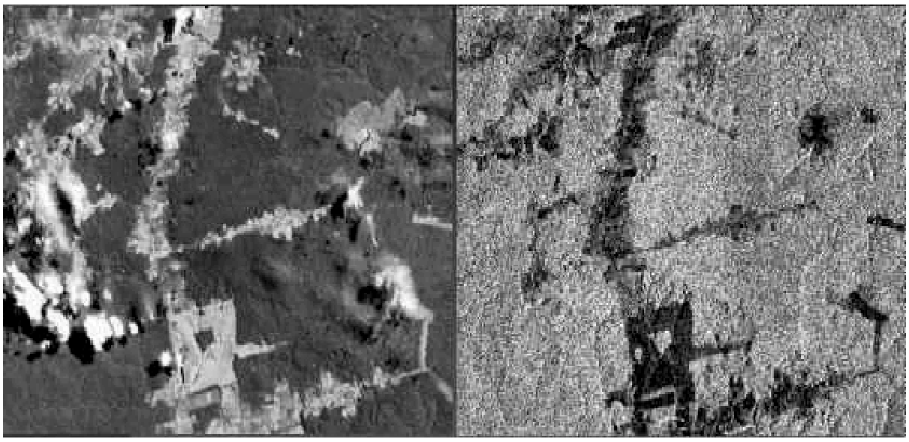

Figure 2: Two images of the same area of the Amazon forest. Left a LANDSAT-TM image, and right a JERS-1 radar image (source: Corina Freitas and Eymar Lopes, INPE).

5 Knowledge Representation on Images

In this section, we propose a multi-level ontology for images, based on the concept of *action-driven ontologies* for GIS [17]. The idea behind action-driven ontologies is that a significant part of geographical knowledge is captured by the procedures that extract information from spatial data sets. The idea is to derive ontologies not only for the objects of the domain (the "nouns"), but also for the intended actions (the "verbs"), which are expressed by the procedures applied to the original data set for knowledge extraction. An additional conceptual framework is Marr's theory of vision which proposes a three-level approach for computer vision, consisting of an *information processing strategy* level, an *algorithms and data structures* level, and a *physical mechanisms* level [18].

We consider that images have an ontological description of their own, distinct and independent from the domain ontology a domain scientist uses to extract information from them (Figure 3).

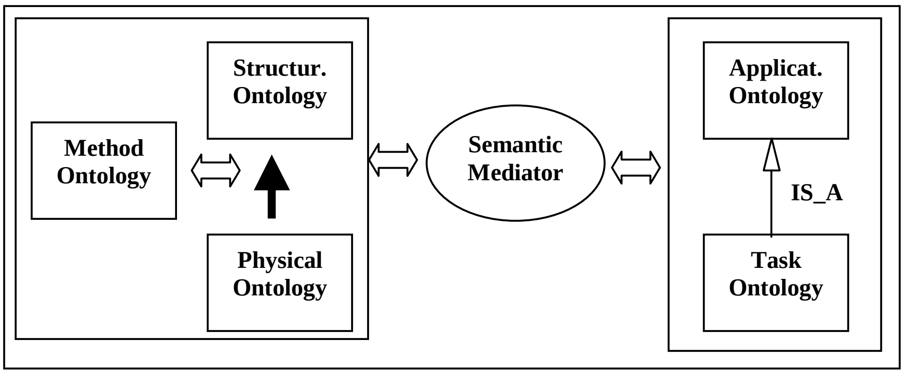

Figure 3: Ontological context for image information extraction

The ontological domain for the images (called *phenomenological domain ontology*) is measurement-dependent. It has three distinct, but interrelated components:

- A *physical ontology*¸ which describes the physical process of image creation. Here we are interested in expressing knowledge about the relation between energy reflected by the Earth's surface and the measurements obtained by the sensor. Typical concepts here include `spectral response`, `backscatter`, and `Lambertian target`.
- A *structural ontology*, which includes the geometric, functional, and descriptive structures that can be extracted from or detected in the image by means of feature extraction, segmentation, and classification techniques. Typical concepts for this ontology include geometries as `lines` and `regions`, and functional descriptions

such as `spectral response curve`, `optical flow`, and `light intensity gradient`.

- A *method ontology*, consisting of a set of algorithms and data structures, which represent reusable knowledge in the form of image processing techniques that can be used to transform the image from the physical level (e.g., by filtering or enhancement) or to perform feature extraction and classification.

The algorithms that are part of the *method ontology*, perform transformations from the physical level to the structural level, a process than can be called *structural identification*. When applied to an image (or a set of images), this process results in a set of *structures* strongly related to the measurement device properties and its interaction with the physical landscape. These structures may be geometric (e.g., regions extracted by a segmentation procedure) or functional (e.g., NDVI estimates obtained from NOAA/AVHRR series of images).

While this phenomenological ontology is observer-independent, the domain scientists operate using concepts from their knowledge domains. Following Guarino [19], we distinguish between a *application domain ontology*, which describes the vocabulary related to a generic domain (e.g., geology or ecology), and *application task ontologies*, which are specializations of the domain ontology, describing a task or activity within such domain, such as water pollution assessment for ecological studies.

For example, research on land use and land cover change uses such concepts as `forest`, `grassland`, `cropland`, `wetland` for land cover and `logging`, `ranching`, and `agriculture` for land use [20]. These concepts belong to the *application domain ontology*, and their relation to the image (*phenomenological domain*) ontology is strongly dependent on the spatial-temporal analysis scale. Large-scale surveys, such as global change mappings, usually preclude the identification of individual objects in the set of images used. In this case, the *applicarion task ontology* might be very similar to the *application domain ontology*. Small-scale analysis of limited geographic areas might require the identification of objects from the *application task ontology* in the image. For example, areas that are classified in the large-scale survey as type `agriculture` might be assigned to specific types of agricultural use (e.g., `soybeans`, `rice`, and `coffee`) in the task ontology used by the small-scale survey.

The application ontologies include two different types of spatial entities: classes of *identifiable objects* (that can be related to *fiat objects* in the image) and classes of *spatial continuous phenomena* (that can be related to temporal series of images that are modeled as fields). The relation between the image ontology and the application ontology is achieved by means of a *semantic mediator*, which performs two basic functions:

- **Identify** what specific image processing and pattern recognition algorithms (described in the *method ontology*) are needed to extract the desired structures from the image or to transform the physical (i.e., pixel) values to obtain the desired information.
- **Map** from concepts on the domain ontology (i.e., objects and fields) onto structures extracted from the image set. For example, a domain ontology may

contain a concept of a `road`. Using the semantic mediator, we may look for identifying `roads` among the `linear structures` that are part of the structural ontology of the image.

The proposed multi-level ontology allows different *application domains* to be related to the same *phenomenological domain*, a perspective that reflects the fact that the same image (or set of images) can be used in many knowledge domains. For example, the same set of images can be used for land use and land cover mapping or for geological studies.

There are many different possibilities for building a semantic mediator. In this paper, we consider the *constructive approach*: an external observer builds the semantic mediator by forming a correspondence between concepts in the *application domain* and concepts in the *phenomenological domain*. We call one such relation a *matching* (by analogy with the matching concept in Image Understanding systems). In a single time-instance, the set of matchings of a concept from the *application domain* onto an instance of a concept on the *phenomenological domain* is called a *spatial configuration.* Given a temporal sequence of images, the set of *spatial configurations* is called a *spatio-temporal pattern*.

Consider the example of mapping deforestation on a tropical forest, as shown in Figure 4. In this image (a LANDSAT/TM color composite for the Brazilian state of Rondonia), a segmentation algorithm has extracted regions from the pixel values [21]. Two distinctly different types of deforestation can be observed: regular square-like patterns (resulting from large cattle ranches) and irregular patterns, resembling fish bones, which result from colonization projects.

In this case, the *application domain ontology* may distinguish generic types of concepts, such as `forest`, `non-forest vegetation`, and `deforested areas`. This latter concept could be specialized into `cattle ranches` and `small farms`. At the *structure ontology* level, we may distinguish such concepts as `region` and its specializations `fishbone region` and `regular region`. In the image, each region will be described by a set of statistical and morphological properties.

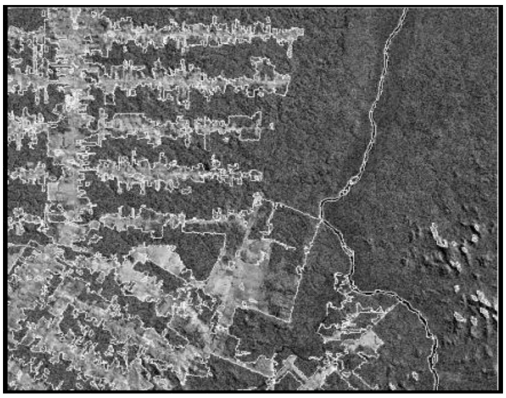

Figure 4: Deforestation mapping with a LANDSAT image (source: Eymar Lopes, INPE).

A mapping between an instance of a concept on the application domain (e.g., `small farm`) and an instance of a concept on the structure domain (e.g., one instance of `fishbone region`) defines a *matching*. The set of all matchings between instances of `fishbone regions` to `small farm` defines, for this specific image, a *spatial configuration*. If we perform this set of matchings in a time-series of images containing deforested regions, we can call the set of *spatial configurations* of (`fishbone region`, `small farm`) matchings a *spatio-temporal pattern.*

By using mediation between the image and application ontologies, we create a framework that emphasizes the detection of *spatial-temporal configurations* of *geographic phenomena*, taken here as identifiable *structural elements* present in an image. This idea is consistent with the identity-based modeling of change [22], where *object identity* is proposed as a central notion for modeling spatial-temporal change. The framework allows an object, identified as part of the user ontology, to be related to different descriptions in an image time series. Consider, for example, mapping urban sprawl for a city by analyzing a 20-year time series of LANDSAT images. The geometries that describe the evolution of the urban boundaries of the city change yearly, yet the identity of the object remains the same.

Another important consequence of the separation of image and application ontologies is the possibility of the same structures be reused by different applications. A simple example is the case of detecting or extracting `line segments` from a series of images. `Line segment` is a concept that is part of the structural ontology of the image. It has clearly defined geometric properties. These lines can take different roles in *domain ontologies* of different user communities.

6 A Representational Framework for the Ontology of Images

In order to translate the concepts proposed above into a computable model, a representational framework is needed to capture the essential dimensions of the ontological model. We consider the case of detection and monitoring of the spatial temporal evolution of *objects*, as defined in the application domain ontology. The case for the detection of *fields* would be similar.

In our framework, data and operations are referenced on an **embbeding space,** mapped to a homogenous 2-dimensional point set S [23]. Images are acquired at discrete instances of time in a linear time sequence. To simplify our formulation, we shall consider the granularity of our time sequence to be equal to the acquisition period for an individual image in our data set. We shall denote the union of all discrete time intervals $\cup t_i$ as T .

Our representational framework consists of the following:

- **Image**: Given a physical ontology PO , an image is defined as

`image`: $[f, t_i, \{po_i\}],\ f : S \subset R^2 \rightarrow R^n,\ t_i \in T,\ po_i \in PO$, where:

f is a mapping between the embedding space S and a set of real values,

t_i is the image acquisition interval, and

$\{po_i\}$ is the set of concepts that defines the physical features of an image.

- **Image sequence**: is a set of *images* defined over S,

  `image_sequence:` $[\{I_i\}]$

- **Geometric structure:** given an embbeding space S, a structural ontology SO and a set of attributes $A_1,\ldots,A_n$, a *geometric_structure* is defined as

  `geom_str` $:[\{P_i\},t_i,\{so_i\},\{a_i\}],\ P_i \subseteq S,\ t_i \in T,\ so_i \in SO,\ a_i \in dom(A_i)$

  where

  $\{P_i\}$ is the set of spatial locations (the union of closed point sets),

  t_i is a time interval, corresponding to the image acquisition reference,

  $\{so_i\}$ is the set of concepts that define the geometric structure,

  $\{a_i\}$ is a set of attribute values $a_1,\ldots,a_n$ whose domains are $D(A_1),\ldots,D(A_n)$.

- **Image processing function**: Given a *method ontology* MO, *an image processing function* maps an image into another image. The signature of these functions is

  `proc_funct:` $[f,\{mo_i\}],\ f:I \to I,\ mo_i \in MO$,

  where

  $\{mo_i\}$ is the set of concepts that define the features of the function.

- **Image classification function:** These functions perform a mapping between an *image* and a set of *geometric structures* in S. One example is a maximum-likelihood pixel classifier. The signature is:

  `class_funct` $:[f,\{mo_i\}],\ f:I \to \{gs_i\},mo_i \in MO$

- **Landscape object:** Given an application domain ontology AO, and a set of attributes $A_1,\ldots,A_n$, a landscape object is defined as

  `landscape_object:` $[\{ao_i\},\{a_i\}],\ ao_i \in AO,\ a_i \in dom(A_i)$

  where

  $\{ao_i\}$ is the the set of concepts that defines the landscape object.

- **Similarity Measure:** we consider two types of similarity measures. The first (sm_1) finds matches between concepts in the application domain ontology AO and concepts in the structural ontology SO, and the second (sm_2) finds matches between concepts in the application domain ontology AO, concepts in the method ontology MO and concepts in the physical ontology PO.

`sim_meas1`: $[f], f: SO \times AO \rightarrow \mathbb{R}$

`sim_meas2`: $[f], f: MO \times PO \times AO \rightarrow \mathbb{R}$

- **Spatial configuration:** given a *landscape object lo*, a spatial configuration is a tuple

  `spt_config`: $[(lo, \{gs_i\}, t_i)]$

  where

  $\{gs_i\}$ is a set of geometric structures in an image *I*

  t_i is a time reference, which is the same as the set $\{gs_i\}$

- **Structural matching**: given a *landscape object*, a *structural matching* generates a set of *spatial configurations*, by applying a similarity measure:

  `struct_matching`: $[sm_1, f], \; f: \{gs\} \times lo \rightarrow \{sc_i\}$

  where

  sm_1 is a similarity measure of type-1,

  $\{gs_i\}$ is a set of geometric structures in an image *I*,

  lo is a specific landscape object,

  $\{sc_i\}$ is the set of spatial configurations produced by *M*.

- **Functional matching**: given a landscape object and a method ontology MO, a functional matching is able to choose an appropriate image classification function, by applying a similarity measure:

  `funct_matching` : $[sm_2, f], \; f: MO \times lo \rightarrow cf$

  where

  sm_2 is a similarity measure of type-2,

  lo is a specific landscape object,

  cf is the selected image classification function which will produce an appropriate set of geometric structures.

- **Spatio-temporal pattern**: given a landscape object and an image sequence, a *spatio-temporal pattern* is the set of all *spatial configurations* for a specific *landscape object* in this *image sequence*.

  `spt_time_pattern`: $[lo, \{I_i, sc_i\}], \; I_i \in Is$

where:

lo is a specific landscape object,

I_i is an image which is part of an image sequence Is,

sc_i is a *spatial configuration* defined over I_i.

To give one exemple in the case of deforestation mapping, a **landscape object** would be an instance of an object defined as `deforested_area`; **an image classification procedure** would be defined the algorithm defined as `isodata_clustering`; a **geometric structure** would be the set of points defined by one cluster obtained by the classification procedure; a **spatial configuration** would be the set of clusters which are mapped to the concept of `deforested_area`, in one specific image; and **a spatio-temporal pattern** would be the set of all spatial configurations mapped as `deforested_area` for an **image sequence** defined over a 10 year period.

A knowledge base built with this framework is flexible enough to integrate different types of sensors, to include new concepts of the application domain, and to incorporate new image processing algorithms. It emphasizes remote sensing images as a support for the *dynamical analysis of the landscape* and has as a central component a set *of spatial-temporal patterns.* The knowledge base could be used by an information retrieval system for extracting patterns in a large remote sensing image database, or by a semantic mediator as a basic guidance for finding similar patterns in new images.

7 Conclusions

This paper has examined an ontology of images. We argued that images have an observer-independent ontological status. Thus, procedures for knowledge extraction on images require a semantic mediator, which establishes a correspondence between instances of concepts in the domain ontology (used by an application researcher) and concepts on the phenomenological ontology (which describes how the image represents the real world). With a clear separation between image and user ontologies, two key benefits are achieved: (1) the support for *multiple perspectives for the same image*; and (2) an emphasis on using images for the detection of *spatial-temporal configurations* of *geographic phenomena*.

In an early paper on integrated GISs, Ehlers *et al.* [24] presented a three-level integration process to be progressively achieved by GIS [25]. They distinguished between a level for simultaneous display of vector and raster data and conversion of pre-processed results, a level for dynamic data exchange with a single user interface, and a level for total integration. The latter would consist of a unique system based on a single model of the world.

Our work has significant consequences for the concept and implementation of such integrated GISs. With images having a separate ontological status from the user domain ontology, some type of semantic mediator will always be needed as a interface between the two ontologies. As a result, the quest for total integration, in the sense that a unique ontology would be used by an IGIS, would be inadequate. Instead, an integrated GIS needs to be based on multiple ontologies so that it could be flexible enough to combine different sets of concepts.

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