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An Intelligent Data Analysis framework for supporting perception of geospatial phenomena

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Abstract. Land use and urban development surveys involve the interpretation of a large volume of data coming from satellite images processing as well as from remote sensors networks. In order to facilitate this interpretation, the development of a multipurpose Intelligent Data Analysis (IDA) framework for supporting geographical data perception is proposed here. The framework makes use of semantic technologies and relies on a novel knowledge model composed by a foundational ontology (DOLCE Ultra-Lite, also called DUL), three core reference ontologies (the Temporal Abstraction Ontology or TAO, the Semantic Sensor Network ontology or SSN and the SWRL Temporal Ontology or SWRLTO) and two specific domain ontologies (the Urban Ontology or URO and the Geographic Data ontology or GeoD, developed by our team). They play different and well specific roles in the whole process of perception. The paper shows how to apply SSN to manage measurements of geographical regions provided by satellite images processing software. In a similar way, TAO has been extended to deal with the abstractions resulting from geographical data interpretation. An example shows a SWRL based implementation of a perception process that gradually abstracts geographical features and objects.

Keywords. Satellite Image analysis, Intelligence Data Analysis, Machine Perception, Ontology, Semantic Sensor Web, SSN, DOLCE

1. Introduction

The understanding of complex phenomena, such as deforestation or urban development, requires geosensor networks observing the Earth at multiple scales and time instants. Geosensor networks are distributed ad-hoc wireless networks of computing platforms serving to monitor geospatial phenomena. This sensing technology has had a big development in the last decades [21]. Geosensors provide every day thousands of Terabytes of geospatial data from every corner of the earth. However the integration and interpretation of these data remain nowadays an unresolved issue.

In this paper we propose to address the geographic data integration and interpretation problem by means of an ontology-based framework. It was developed as an extension of the approach presented in [24]. The framework relies on the modelling of percep-

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tion tasks. A novel knowledge model composed by six ontologies semantically aligned has been developed with that aim. The knowledge representation of geographical qualities, geographical objects, observations and perceptions were resolved by means of well known ontologies and new conceptualizations.

Instead of trying to cope with a specific domain problem, this work aims to show the main components and capabilities of the proposed solutions that could be useful to address different geographical surveys. The paper is organized as follows. Section 2 gives the theoretical background of these works, then the semantic perception scheme on which this work is based is described (Section 3). The components, features and requirements of an Intelligent Data Analysis (IDA) framework are stated in Section 4. Section 5 presents the main knowledge representation aspects and two illustrative examples are also presented. Finally, the conclusions and perspectives of future work are given in Section 7.

2. Theoretical Framework: Machine Perception and Intelligent Data Analysis

The final goal of a computer-aided data interpretation approach is to achieve human perception-like capabilities.

Perception is the ability to become aware of things through the senses. Therefore, it can be considered as the process of taking a set of observed qualities and deriving abstractions from them. This definition involves three concepts that are key for the modelling of perception processes: *perception*, *observation* and *abstraction*. Although observation and perception are often considered as equivalent concepts, they refer to different cognition skills. *Observation* is a process (mostly physical) by which an agent (people or machine) detects the features of its environment by using sensory skills (e.g. visual, auditory, olfactory, tactile, etc). On the other hand, *perception* is the process of adding meaning to stimuli. Hence, while *perceptions* are views of the reality that depend on the context, the belief and the goal of the one who perceives, *observations* provide a set of unbiased measurements (mostly quantitative values) of the real world properties.

Finally, an *abstraction* provides a value (mostly qualitative) that interprets the state of a property of a real world entity (physical, abstract, an event, etc.) that was perceived [14]. Abstractions can have a wide range of complexity, from relatively low level abstractions up to complex and high-level ones based on combinations of other more primitive abstractions [18,25,20].

The main difficulties underlying the perception functions are the so-called symbol anchoring tasks. These tasks establish correspondences between the sensor data and the symbols that represent abstractions of what has been observed [8].

Although there are several techniques to tackle this problem, the ones based on semantic characteristics and contextual information are the best adapted, because they are transparent for the user, in the sense that they permit to keep a log of the perception tasks and to maintain the consistency of the whole knowledge involved in these tasks.

The main goal of intelligent data analysis is to address the aforementioned aspects. IDA is an emergent research field combining different tools such as statistics, pattern analysis, machine-learning or data mining to reduce the gap between the data generation and their comprehension [2]. Unlike Knowledge Discovery in Databases (KDD) that deals with learning new knowledge from databases, IDA focuses on the application of knowledge for data interpretation [17].

3. A Semantic Perception Scheme

The machine perception method supported by the proposed framework is based on three main principles:

- The geographic object-oriented analysis approach
- A gradual bottom-up abstraction process
- Qualitative representation and reasoning

3.1. Geographic Object-Based Image Analysis

Geographic object-oriented analysis (GEOBIA) focuses on the interpretation of the semantics underlying a spatially referenced imagery [3]. It combines GIS, remote sensing and image processing tools to derive meaningful objects from the processed images. Aiming at imitating human perception, GEOBIA works by dividing images into meaningful objects and abstracting more intuitive features such as shape, size, pattern, tone, texture, shadows and their associations. In general, GEOBIA follows three steps: segmentation, feature estimation and classification; which are often preceded by some ancillary pre-processing and/or followed by an accuracy assessment step. GEOBIA leverages the use of contextual information and domain knowledge which is not always explicitly contained in the image [26].

3.2. A Gradual Bottom-Up Abstraction Process

Human beings perform a gradual bottom-up abstraction process to interpret what they observe. This is a well known cognitive model that has proven to be useful in the design of semantic-based perception models [15]. This process progressively interprets the measured data and generates abstractions which are then used as input to perform new interpretations (see Figure 1). Applied to geographic data analysis, at each level this method uses the regions qualities in order to derive more qualities of them or of other entities at a higher abstraction level. In that way, abstraction at the lowest levels such as “big”, “vegetable”, “rectangle” (also known as features) are used to produce higher level abstractions such as “Forest” or “Road” that bring more meaningful descriptions of the observed entity.

3.3. Qualitative Representation and Reasoning

Qualitative Representation and Reasoning (QRR) plays an important role in perception functions. By using qualitative qualities such as “small”, “short”, “dark”, QRR helps to embrace data complexity and dimension, and improves the simplicity of IDA implementations in data intensive environments [28]. With the use of QRR, the IDA system can exploit the capabilities of any symbol-based reasoning scheme (e.g. propositional logic, first-order logic, description logic, etc); to bring a transparent way of capturing perception processes [28].

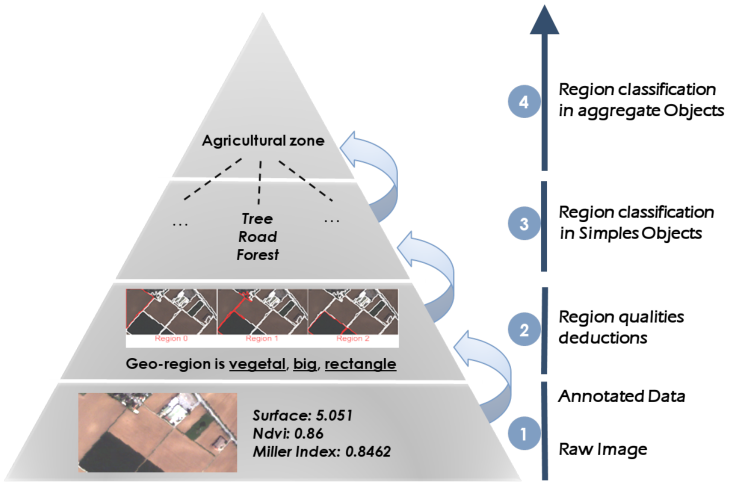

Figure 1. Bottom-up abstraction process

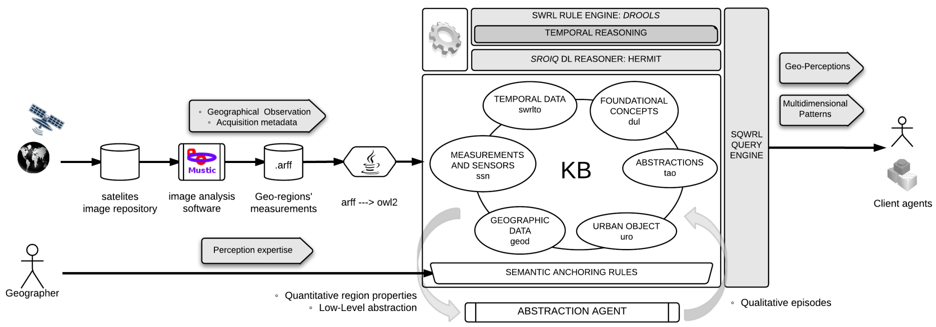

Figure 2. GIDA-Framework

4. The Geographic IDA System Design

In this work, the general IDA framework presented in [24] is enhanced to support geographic data analysis. We call it Geographic IDA or GIDA.

Figure 2 depicts the work-flow in the proposed framework. The input data are high resolution remote sensing images, coming from specific satellites (e.g. IKONOS [16], ASTER L1 [1], SPOT [10], Landsat 7 [5]). Images are provided at different resolutions and spectral bands. They have some built-in meta-data such as the GPS coordinates and the time of capture. After capture, images usually require some pre-processing tasks such as filtering and distortion corrections. They are stored in large repositories and then processed by software for image analysis. For experimental purposes, Mustic v6[2] has been used in this work. Through the OTB[3] library, Mustic is able to perform many image segmentation algorithms and to measure several geometric and spectral properties of the

[2] http://icube-bfo.unistra.fr/fr/index.php/Plateformes
[3] Orfeo ToolBox: https://www.orfeo-toolbox.org/

resulting regions. Mustic stores these measurements as ARFF files. After that, a java based agent specially developed for this project transforms the ARFF records into OWL[4] instances (i.e. ontology individuals). As depicted in figure 2, the proposed knowledge model is composed by a set of six ontologies:

1. Semantic Sensor Network (SSN): This ontology provides a domain-independent and end-to-end model for sensing applications by merging sensor-focused (e.g. SensorML), observation-focused (e.g. Observation & Measurement) and system-focused views [7].
2. Temporal Abstraction Ontology (TAO): An ontology for perception modeling representing abstractions for different representation schemes and abstraction levels [24].
3. SWRL Temporal Ontology SWRLTO: An ontology for temporal modeling and reasoning. SWRLTO implements a set of Allen-based SWRL built-in predicates to handle temporal relations [23].
4. Geographical Data Ontology (GeoD): A domain ontology about properties of geographical regions, such as *surface*, *diameter* or *spectral value*.
5. Urban Ontology (URO): A domain ontology that classifies urban objects, including concepts such as *swimming pool*, *warehouse* or *farm* [9].
6. DOLCE+DnS Ultra-Lite ver 3.27 (DUL): It is a simplified version of DOLCE [19] that provides a sound model of upper-level concepts.

These ontologies are semantically aligned to constitute a new ontology called GIDA. The adopted knowledge base structure (composed by six ontologies) responds to the ontological principles proposed by Gruber[13] and the development methodology presented in [22]. The principal criteria has been to reuse recognized ontologies that comply to our needs, thus enhancing interoperability and data integration capabilities. In addition, we wanted to take the advantage of a modular knowledge model.

In this framework the responsibility of performing the symbol anchoring tasks lies in a specialized agent (i.e. *Abstraction Agent*) that must be trained to detect and interpret geographic features. *Abstraction agents* take raw data and/or abstractions as inputs and generate qualitative episodes at a higher level of abstraction. The *abstraction agent* role can be played by a data mining application or by a human expert. Anchoring tasks can be also supported by semantic rules as it will be shown later. These semantic rules are not necessarily obtained from an exhaustive knowledge acquisition job, but they can be generated by inductive approaches, also. The reasoning tasks are performed by different inference engines (depicted on top of Figure 2). A description logic (DL) reasoner maintains the knowledge base (KB) consistency and provides a sound and complete classification scheme with satisfactory measures of computer complexity. Since typical DL reasoners (such as Pellet, Hermit, etc) are not able to process temporal dimensions or to generate new instances (this is necessary to create abstractions), a SWRL-based rule-engine (i.e. Drools[5]) is also required. This environment provides a temporal reasoning layer through a set of SWRL built-in functions that implements Allens temporal operators.

Finally, a query engine is included so as client agents are able to perform queries about the measurements and perceptions of the geographical regions.

[4]Web Ontology Language: `http://www.w3.org/TR/owl2-overview/`

[5]`http://www.drools.org/`

5. Knowledge Representation

The knowledge base is composed by six ontologies. The three core reference ontologies (TAO, SSN and SWRLTO) and the two domain ontologies (GeoD and URO) are aligned thanks to the DUL ontology. This means that the each domain concept is subsumed by a foundational concept of DUL. DUL was chosen as upper ontology because of several reasons. Firstly, as a DOLCE-based conceptualization, its representation schemes enhance the domain concept definitions doing them more precise and formal, so as to avoid ambiguities in their interpretation. In addition, DUL schemes are general enough to cover many domains, thus fostering further alignment and reuse. Finally, DUL has already been chosen by the W3C Incubator Group in the development of SSN (one of the main components of the GIDA framework).

The alignment details in [24] explain how the core concepts of TAO and SWRLTO are aigned with the DUL ones.

5.1. Geographic Objects and Qualities

To support the land use analysis of urban zones, the Urban Ontology (URO) has been used [9]. URO was developed to support urban entities detection (e.g. buildings, roads, parks, etc) using qualitative features of geographic regions. As in our approach, it is based on the GEOBIA scheme and uses processed satellite images as input for classification purposes.

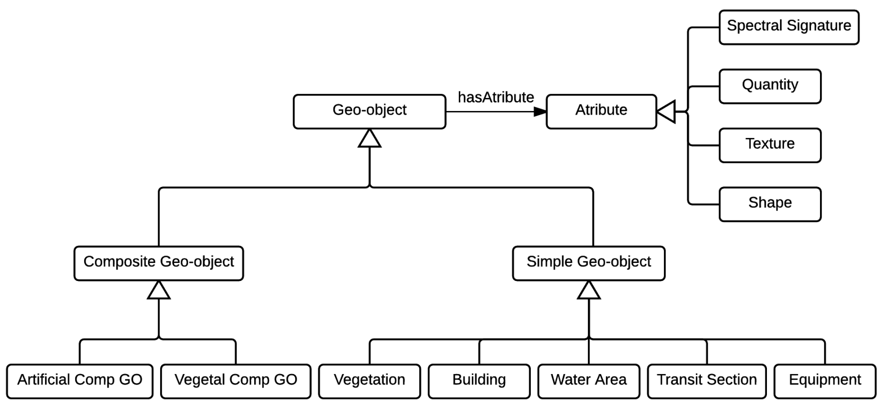

Figure 3. A subset of the conceptualization of the Urban Ontology

Figure 3 shows some of the main classes and properties of the URO using the UML notation. The ontology provides a sound hierarchy of geographic objects or *geo-objects* (not fully depicted in the picture). The first level of the hierarchy has two disjoint classes representing simple objects such as a house or a tree and composite ones whose identity depend on the existence of a groups of smaller objects contained in it (e.g. neighborhoods or parks). A *geo-object* is considered here as any delimited physical entities in the earth surface (e.g. a house or a road).

The class *Attribute* and its subclasses represent a set of qualitative qualities that can be assigned to a *Geo-Object*. The model also includes a hierarchy of object properties subsumed under *hasAttribute* that links the object with its quality values (see Figure 5).

However, since in our approach the conceptualization is based on DUL patterns, the quality representation scheme must fit within the DOLCE design principles [19]. In DOLCE, the quality representation is inspired by [12] and the so-called *trope theory* [6] (see Figure 4). This theory makes a distinction between a *quality* (e.g., the diameter of a building), and its "value" or *quale* (e.g., a number denoting a measure in metrical unit). In DOLCE, *qualities* are particulars (i.e. instances) that inhere to specific entities; that is, a quality exists as long as the entity exists. On the other hand, a *quale* describes the position of an individual quality within a certain conceptual space (also called *quality region*) [11].

To apply this scheme to the URO conceptualization, a class has been created for every object property in the *hasAtributte* hierarchy. These classes (representing quality types) are included in the GeoD ontology and must contain different instances for different geographical objects.

A highlight of this scheme is that it can explain different roles of qualities; for instance, "shape" is a property of geo-objects (e.g. *reg100 hasProperty shape100*) but it is also a "geometric thing" (i.e. *Shape* is subsumed by *Geometric Quality*). Moreover, the approach allows to declare and to reason with *Geo-Objects* properties even when their values are unknown. For instance, it is possible to express that a building has a height (this is not the case for a road, for example) even when it is not possible to get the precise value.

It is important to remark that, in our approach, the bounds between qualities and their corresponding values are stated indirectly through a perception process. This means that the value of a quality necessarily depends on the existence of an agent that determines it by interpreting real world phenomena. Hence in our model, there is an intermediate concept bounding a quality with one or more qualias; each one corresponding to different spatio-temporal locations, agents and abstraction levels. This approach allows several reality views to be represented in the same knowledge conceptualization. These views, that in a traditional object-property modeling would be considered inconsistent, here reflect alternative interpretations of the world.

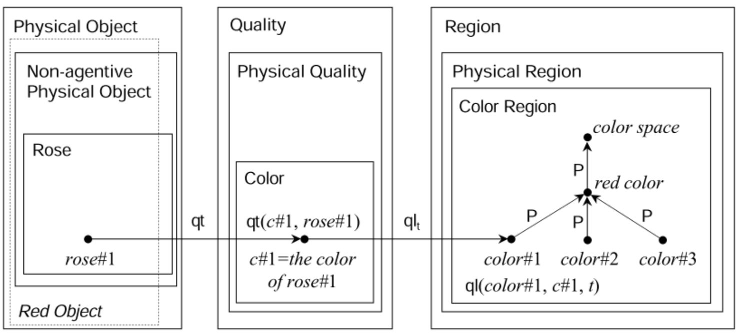

Figure 4. DOLCE quality representation scheme
[19]

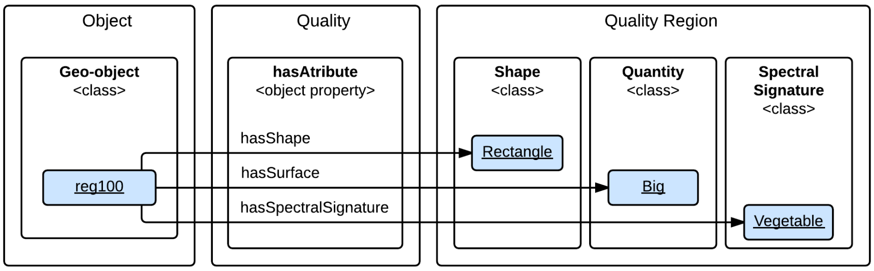

Figure 5. Urban Ontology quality representation scheme

5.2. Geo-Region Measurements

As described above, the knowledge base is first populated with a set of geometric and spectral properties measurements of geographical regions. To model these observations we have imported and extended the Semantic Sensor Network (SSN) ontology. SSN targets the formal and machine-processable representation of sensor capabilities, properties, observations and measurement processes. SSN allows the network, its sensors and the resulting data to be organized, installed and managed, queried, understood and controlled through high-level specifications. The SSN ontology has implied a large conceptualization effort to merge sensor-centric and observation-centric approaches. In addition, SSN leverages the Sensor Web Enablement (SWE) standard proposed by the Open Geospatial Consortium[6] [4].

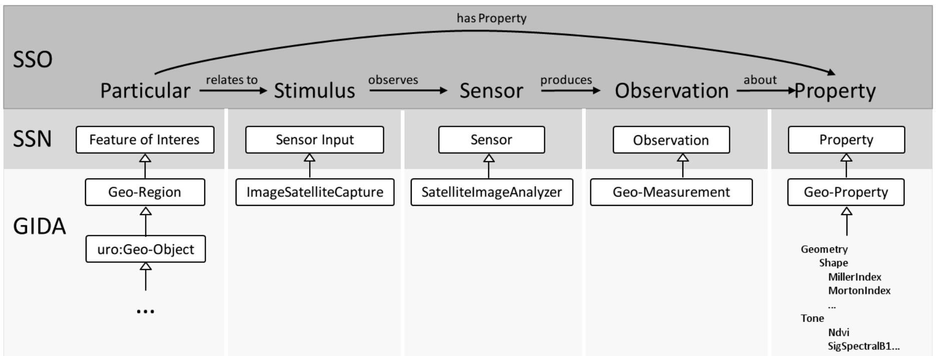

Figure 6. Extension of SSN by applying the SSO pattern to geo-region measurements

The SSN ontology implements the *Stimulus-Sensor-Observation pattern* (SSO) presented by [27]. It introduces a minimal set of classes and relations centered around the notions of *particular*, *stimuli*, *sensor*, *observation* and *property* (see Figure 6). *Particulars* (in SSN represented by *ssn:Feature of Interest*) are entities that are the target of sensing. A particular definition depends directly on the observation goal and it can be an event or an object (physical or abstract). *Stimuli* are detectable changes in the environ-

[6] `http://www.opengeospatial.org/`

ment that a sensor observes to infer information about environmental properties. It means that sensors are not able to get knowledge directly from a particular, and thus *Stimuli* play the role of a link to the physical environment. In SSN, *Stimuli* are represented by the equivalent classes *ssn:Stimuli* and *ssn:SensorInput*. *Sensors* (in SSN, *ssn:Sensor*) are entities that transform an incoming stimulus into another representation. *Observations* (in SSN, *ssn:Observation*) act as nexus between the stimuli, the sensor, and the output of the sensor, i.e., a symbol representing a region in a dimensional space. *Properties* (in SSN, *ssn:Property*) are qualities of particulars that can be observed via stimuli by a certain type of sensor.

However, although SSN is mostly directed toward physical devices that detect physical properties, here it is proposed to capture the results of an image processing software whose inputs are satellite images. In order to extend SSN to this particular application, it is needed to establish how the new entities fit in the SSO pattern. The proposed alignments are depicted in Figure 6. In this domain it is not possible to state an universal entity for *Particulars* since they depend on the aim of the geographical survey. For example, we could be interested in the land use of a delimited area or in the habitat of an animal or species, in which case the nature of the region boundaries, position and shape are totally different. However, as our first experiments are directed towards urban object recognition, two classes have been proposed for this category: *Geo-Region* represents any delimited region on the earth surface, no matter if it matches with a geographical object or not. On the other hand, the *Geo-Object* class (already defined in URO, see previous section) has been subsumed by a *Geo-Region*, meaning that objects are particular regions whose features match with a predefined semantics (e.g. a *park* is "an urban region, often of forested land, maintained as a place of beauty or for recreation"). With regards to the *Property*, a class hierarchy has been developed representing the quantitative attributes of geo-regions. The forty-one measurements provided by Mustic have been considered, among them several indexes of size, shape and tone. These classes are part of GeoD ontology and are subsumed under *geod:Geo-Property* and *ssn:Property*. In the same way, *ssn:Observation* has been extended by a set of classes representing the different types of measurements (e.g. *SurfaceMeasurement*, *DensityEstimation*, *NdviComputation*, etc). In this application, since the sensor is an image processing software, a new subclass of *ssn:Sensor*, called *SatelliteImageAnalyzer*, has been added. The *Stimuli* or input of the observation process is a satellite image. It is modeled by the class *ImageSatelliteCapture* whose instances are linked (by data properties) with the image metadata (i.e. geoposition, resolution, dimension, time of capture).

It is to be remarked that this study is not only valid for observations modelling, it is also important to represent perceptions since our perceptions model relies on the same concepts of *Particulars* and *Properties* as it is explained in the next section.

5.3. Geographic Perceptions

In order to model the entities involved in the geographic perception process, the Temporal Abstraction Ontology (TAO) has been imported and extended. Figure 9 shows a fragment of the TAO conceptualization in an instantiation example.

The main component of this conceptualization is the concept of *Episode*. *Episodes* are abstractions of data stream slices obtained by a heuristic or formal method. They are formally defined as a set of two elements: a time interval, named a temporal extent, and a qualitative context, thus providing the temporal extension with significance [29]. The temporal extent is given by a *swrlto:ValidTime* while the qualitative context is given by a *tao:Primitive*. Like *ssn:Observation*, *tao:Episode* is associated with the *Property* (i.e. *geod:Geo-Property*) and a *Particular* (i.e. *geod:GeographicRegion*).

Primitives are the elemental symbols of the alphabet used for a given qualitative representation scheme (class *tao:QR Scheme*). Each primitive has a predefined semantics that brings an interpretation of the underlying phenomena. An episode of a *QR Scheme* is characterized by a single primitive and it is represented by the object property *tao:hasPrimitive*.

As mentioned before, the class *uro:Attribute* in the URO and its subclasses constitute a dictionary of qualitative primitives for characterizing geographical regions. Therefore, the classes have been reused by aligning them to TAO model as is shown in Figure 7.

The class *tao:TA Representation Agent* has been defined in order to trace the abstraction process. *tao:TA Representation Agent* represents the abstraction agent depicted in the Figure 2.

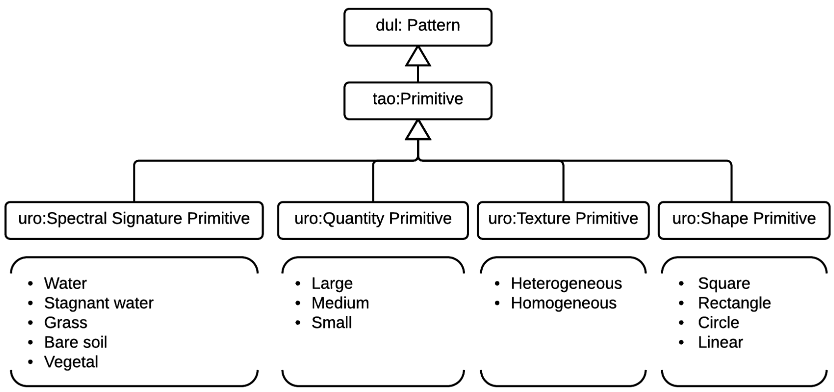

Figure 7. Integration of qualitative geographic primitives to TAO

6. Implementation Example

This section illustrates the use of the proposed knowledge model and the implementation of a gradual perception process based on SWRL rules.

Figure 8 shows the specification of the normalized difference vegetation index (NDVI) over a region of Strasbourg city (France) using the presented ontology. The computation was performed by Mustic over a satellite image captured in 2014. The white boxes represent classes while the underlined names are instances. These observation data are located at the first level of the abstraction process depicted in Figure 1.

NDVI is a well known index that helps geographers to deduce the land cover elemental class of the observed region. For example, a region may be considered as a vegetation area if it satisfies the following rule:

```
IF (ndvi > 153.6) THEN Elemental Class = "Vegetable"
```

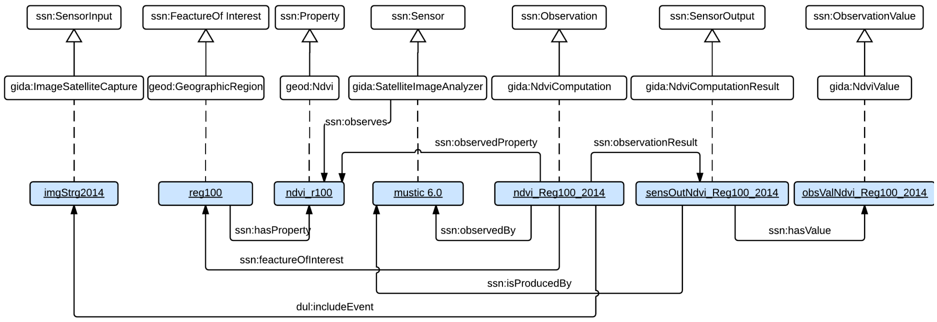

Figure 8. Representation of a geo-region NDVI measurement using SSN

This rule can be integrated to the KB using SWRL. Then a rule engine such as Drools can be used to automatically derive the elemental classes of the geographical regions. Given the presented conceptualization the rule is expressed as follows:

```
ssn:featureOfInterest(?x, ?y) ,
ssn:observationResult(?x, ?r) ,
ssn:hasProperty(?y, ?ec),
geod:Elemental Class(?ec),
ssn:hasValue(?r, ?v) ,
dul:hasRegionDataValue(?v, ?dv)  ,
swrlb:greaterThan(?dv, 153.6) ,
swrlx:makeOWLThing(?p, ?x) ->
tao:Episode(?p) ,
tao:hasPrimitive(?p, vegetable) ,
tao:featureOfInterest(?p, ?y) ,
tao:isEpisodeOf(?p, geo_ElementalClassScheme) ,
tao:isAbstractionOf(?p, ?x) ,
tao:hasEpisode(?ec, ?p) ,
tao:obtainedBy(?p, swrl-based_agent)
```

In order to generate new OWL individuals, this rule makes use of the *makeOWLThing*() SWRL built-in function. It is provided by the *SWRL Extensions built-in library*[7].

It is to be remarked that the application of rules like this to observation records permits to go from the first level to the second level of abstraction in the bottom-up abstraction process presented in Figure 1.

Figure 9 shows the ontology instantiation that results from the execution of the rule to the same region of Figure 8.

Using qualitative features such as "vegetable" further interpretation tasks can recognize and classify geographical objects in the analysed image. These tasks constitute a second step in the perception process illustrated in Figure 1 (i.e. from the second level to the third level) and can be also supported by a SWRL rules as follows:

```
GeographicRegion(?x) , ssn:hasProperty(?x, ?p1) ,
GeoElementalClass(?p1) , tao:hasEpisode(?p1, ?e1) ,
tao:hasPrimitive(?e1, vegetable) ,
ssn:hasProperty(?x, ?p2) , Large(?p2) ,
tao:hasEpisode(?p2, ?e2) ,
```

[7] http://swrl.stanford.edu/ontologies/built-ins/3.3/swrlx.owl

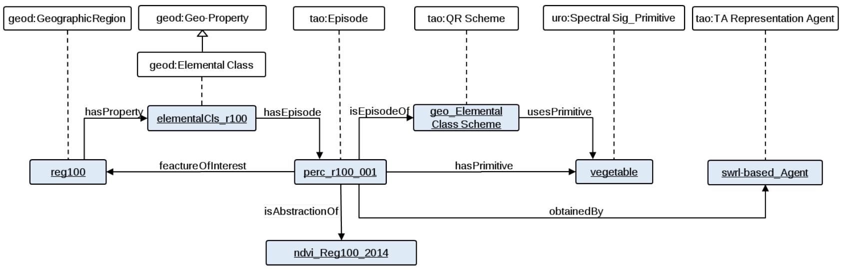

Figure 9. A geographic perception using TAO. A SWRL-based agent infers the land cover elemental class of region *r100*

```
tao:hasPrimitive(?e2, small) ,
ssn:hasProperty(?x, ?p3) , Shape(?p3) ,
tao:hasEpisode(?p3, ?e3) ,
tao:hasPrimitive(?e3, circle),
swrlx:makeOWLThing(?ex, ?x) ->
tao:Episode(?ex),
tao:featureOfInterest(?ex, ?x) ,
tao:isEpisodeOf(?ex, geoObjectClassScheme) ,
tao:hasEpisode(geoObjectClass , ?ex) ,
tao:hasPrimitive(?ex, tree) ,
tao:isAbstractionOf(?ex, ?e1) ,
tao:isAbstractionOf(?ex, ?e2) ,
tao:isAbstractionOf(?ex, ?e3) ,
tao:obtainedBy(?ex, swrl_engine)
```

This kind of rules makes use of geometric and spectral qualitative features to identify geographic objects. In particular, this rule creates the abstraction “tree” for the property *Class* of a geographic region if it has been previously characterized as a small and circular zone with vegetation.

7. Conclusions and Future Works

In order to support the integration and interpretation of geographic data, an ontology-based Intelligent Data Analysis framework has been presented. It relies on six ontologies semantically aligned under the foundational concepts of DOLCE Ultra Lite.

The SSO pattern has been used for extending the SSN ontology to capture geometrical and spectral measurements computed by satellite images processing software, as well as for modeling abstractions derived from data interpretations.

The proposed machine perception scheme is based on a cognitive model that gradually generates interpretations at higher levels of abstraction. In this way, a complex perception problem is disaggregated in many symbol anchoring tasks that are simpler as they aim at filling smaller semantic gaps.

The presented ontology stores and manages the whole knowledge involved in this process including the sources of observation (i.e. raw satellite images), the sensor measurements (e.g. the size or shape of the geographical regions), the inferred abstractions at each level, the perception agents and methods, etc. Moreover the model stores the links between the observations and their interpretations.

This ontological modeling features aim at bringing a transparent data analysis environment that enables outputs to be traced from the high level abstractions to the raw sensor data, going through all the intermediate interpretation tasks. Transparency and understandability are the highlights of this approach that cannot be provided by most of black-box solutions such as the ones implementing pure machine learning-based methods.

Although just static abstractions have been considered in this work, it should be remarked that the GIDA framework also enables temporal representation and reasoning in order to manage qualitative temporal patterns. Our research group is actually working on the detection of temporal geographical phenomena such as urbanization or deforestation on series of satellite images. With this aim, our future works also involve the use of a spatial reasoning schemes to compute spatial relations within geo-regions (e.g. contains, overlaps, etc).

Another issue that will be object of further work is how to deal with the uncertainty involved in perceptions. Anchoring rules such as those showed in the previous sections are hardly deterministic, and they usually have an associated measurement of uncertainty.

8. Acknowledgments

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