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Towards a semi-automatic semantic approach for satellite image analysis

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Abstract

The extended use of high and very high spatial resolution imagery inherently demands the adoption of classification methods capable of capturing the underlying semantic. Object-oriented classification methods are currently considered the most appropriate alternative, due to the incorporation of contextual information and domain knowledge into the analysis. Integrating knowledge initially requires a detailed process of acquisition and later the achievement of a formal representation. Ontologies constitute a very suitable approach to address both knowledge formalization and exploitation. A novel semi-automatic semantic approach focused on the extraction and classification of urban objects is hereby introduced. The use of a three-layered architecture allows the separation of concerns among knowledge, rules and experience. Knowledge represents the fundamental layer with which the other layers interact. Rules are meant to derive conclusions and make assertions based on knowledge. Finally, the experience layer supports the classification process in case of failure when attempting to identify an object, by applying specific expert rules to infer unusual membership.

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Keywords: object-oriented image analysis; ontology; ontology reasoning, expert knowledge

1. Introduction

In the last few decades, the use of high and very high spatial resolution imagery has become widely extended. The increasing level of resolution has led to some rising complexities in spectral analysis [1] and sometimes the persistence of the mixed-pixel problem [2 - 3] – when a pixel falls into two adjacent objects – . Hence, the availability of high resolution imagery triggers an inherent need for very accurate, efficient and robust classification methods. Pixel-based classification methods are insufficient to meet this demand. A major

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drawback is the "salt and pepper" effect, in which single pixels are classified differently than the surrounding area preventing the generation of homogenous regions [3].

Object-oriented analysis focuses on the interpretation of the semantic underlying in an image. Aiming at imitating human vision perception, this approach works dividing images into meaningful objects and abstracting more intuitive features as a result [3]. One of its main advantages is the incorporation of contextual information and domain knowledge to the analysis, since the semantic is not always explicitly contained in the image [4]. This considerably helps to bridge the semantic gap issue, which rises due to the difference in levels of abstraction. It stands as the lack of concordance between the information extracted from the visual data and the interpretation a user may infer from them in a given situation [5].

An object-oriented image analysis approach normally follows two basic steps: segmentation and classification, which are often preceded by some ancillary pre-processing and/or followed by an accuracy assessment step. The selection of an appropriate segmentation algorithm is a key factor in order to achieve a successful identification of the objects encompassed in a given image. Sets of adjacent pixels should be gathered together as homogenous segments from which meaningful objects could be derived afterwards. Yet, the definition of the term "meaningful object" encloses some ambiguity [3], since boundaries in nature are rarely hard and transitions in land cover may be clear, although usually soft.

Regarding the incorporation of knowledge, a current tendency for knowledge formal representation is the implementation of ontologies, along with sets of logic rules for its management and exploitation. Ontologies are largely described in [6 - 8]. Basically, they are defined as conceptualizations of certain reality or domain designed for a specific purpose. Nevertheless, the reason why they are highly appropriate for knowledge-based systems is their ability to learn, i.e. to incorporate new statements derived from experience.

Several efforts have been done to delineate strategies combining object feature extraction from remote sensing imagery with the implementation of ontology-based classification methods. We highlight here the propositions that seem pertinent to tackle the semantic gap problem. Puissant et al. [4] made use of data mining processes for multi-level interpretation of multi-source images. Metral et al. [9] proposed an urban ontology connected to CityGML to build a 3D city model. Forestier et al. [10] implemented an automatic region labeling method, by assigning segmented regions from an image into semantic objects contained in a knowledge-base.

Also, Fonseca et al. [11] proposed an ontology-based Geographic Information System (GIS) acting as a system integrator. In this system, the ontology is a component, same as the database, cooperating to fulfill the system's objectives. Uitermark et al. [12] proposed a framework for ontology-based geographic data set integration. Ontologies are used here as a collection of shared concepts. Maillot and Thonnat [13] suggested an object categorization involving different aspects of cognitive vision such as learning, recognition and knowledge representation. Their approach is a visual concept ontology composed of several types of concepts (spatial concepts and relations, color concepts and texture concepts). Visual concepts contained in this ontology can be seen as an intermediate layer between domain knowledge and image processing procedures. Pereira dos Santos Silva and Câmara [14] proposed an architecture to help specialists get high level information from satellite data. In addition, there exists the Towntology Project [15], whose goal is to increase knowledge and promote the use of ontologies in the domain of Urban Civil Engineering projects, in order to facilitate communication among information systems, stakeholders and urban specialists at a European level.

In this article, we propose a novel approach to tackle the semantic gap problem, by means of a three-layered (knowledge, rules, experience) semantic architecture. In the short term, this architecture will enable the automation of the whole image analysis process, since knowledge capitalization techniques will be used to keep track of new expert knowledge that has not been represented in the knowledge and rules layers.

The article is organized as follows: section 2 introduces the proposed architecture whereas section 3 describes in detail the three layers. Section 4 presents our first experiments and results and finally, section 5 states our conclusions and perspectives of future work.

2. Our proposal

Modern knowledge engineering practices support the early criteria held in the eighties, based on a layered architecture for the development of intelligent systems, which separates domain knowledge from the reasoning mechanism [16]. This division is thus held in our ontology-based approach, where the first layer corresponds to knowledge stored in the form of logic statements, and the second layer contains the necessary rules to manage and exploit such knowledge. We particularly focus on the implementation of a domain-specific ontology, due to its remarkable suitability for sharing concepts and relations in a certain domain of interest [16].

In our attempt to achieve an optimal performance during object classification, we incorporate an additional layer, which represents the experience acquainted by experts in the knowledge domain. After running the classification step and failing to identify some segmented regions, the statements contained in this layer should be queried in order to derive non-usual membership. For instance, if an unidentified region corresponds to a swimming pool in a backyard, then some additional knowledge based on the expert's experience could help recognize it in this last instance. An important contribution to this perspective is introduced in Sanchez et al. [17], who propose the use of a four-layered model applied to the medical domain, namely: Knowledge, Rules, Experience and medical Guidance. Our work dismisses the fourth layer, since its utility lies in the cyclic nature of the clinical decision support system (CDS) implementation. Our approach, on the other hand, flows in a linear manner, querying the knowledge-base with logic rules in the first place and, in case of failure, consulting the experience layer afterwards. Fig.1 presents the proposed three-layered architecture. Further details of each layer will be given in the next section.

Despite the fact that all the studied methods in section 2 are based on ontologies, none of them uses a real semantic approach aiming to automate, as far as possible, the image analysis process. From our point of view, only the proposal of Forestier et al. [10] seems close to our approach. However, these authors do not separate domain knowledge from the reasoning mechanism. With our three-layered architecture, changes in a single layer, e.g. replacing the urban domain ontology by an erosion ontology, would not affect the remaining layers, enabling the continuous operation of the system. On the other hand, new rules could be added without modifying the representation of the concepts in the knowledge layer. This separation of concerns entails a significant advantage compared to other perspectives: the possibility to undertake knowledge sharing in a straightforward manner. Knowledge regarding a specific domain may be shared among different ontologies operating with their own rules over the same knowledge base. This is feasible as long as some ontological commitments are set among the participating agents [7], [8], i.e. agreements to allow communication in a coherent and consistent manner via a shared vocabulary. Finally, the experience layer will contribute to make the results of the inferences more pertinent and accurate, by allowing a continuous enrichment of the knowledge accessed by the system.

Experience Layer
Expert knowledge which is not explicit in the other two layers. After the system fails to classify a segmented region as a specific geographic object, a group of experts intervenes in the process. This new knowledge will be grasped within this layer

Rules Layer
Rules support reasoning concerning spatial relationships among geographic objects. They also contribute in solving the symbol anchoring problem and in the short term will include expert (generally fuzzy) rules about layouts of cities from different regions.

Knowledge Layer
Contains knowledge regarding geographic objects, including regions, parcels of land and water-bodies, roads, buildings, etc. These objects are typically complex , bound to a minimal scale and hold spatial relationships with one another

Figure 1: Three-layered architecture proposed for (semi) automatic satellite images analysis

3. The three-layered model

3.1. Knowledge layer

Due to the lack of consensus for knowledge representation in the AI field, Newell introduced the notion of the knowledge level, which should lie upon the level of symbols in intelligent systems. Newell [18] defined the system at the knowledge level as an agent, whose structure basically comprises bodies of actions, knowledge and goals. The first one stands as the physical body, with which the agent can act in the environment. The body of knowledge acts, in terms of behavior - not structure -, as a memory: whatever the agent knows at some time it will continue to know, while actions can add new knowledge to the existing body. Finally, the body of goals concerns with states of matters in the environment. The behavior of an agent is governed by a principle of rationality, which argues that if an agent has knowledge that indicates that one of its actions will lead to one of its goals; the agent will then select that action.

Despite the primitive architecture formerly described, the construction of intelligent systems does not follow a standardized recipe. The creation of ontologies that accurately represent a specific domain of interest not only relies on following the appropriate steps during its development, but also depends on a meticulous process of knowledge acquisition. Several authors describe knowledge acquisition as a key phase [6], [19], [20] especially concerned with the knowledge level, i.e. independent from coding language implications.

The challenge underlying in this task is the difficulty for domain experts to transfer knowledge and expertise properly to knowledge engineers [21]. Also, there exists an inherent complexity when adjusting the information acquainted into the formalisms required for machine interpretation.

In our approach, we make use of the urban objects classification held in Cravero et al. [22], based on typologies defined in urban GIS platforms characterizing western cities. Primitive non-decomposable objects are defined as single objects, whereas compositions of singular and/or composite objects are classified as aggregate objects (Fig. 2).

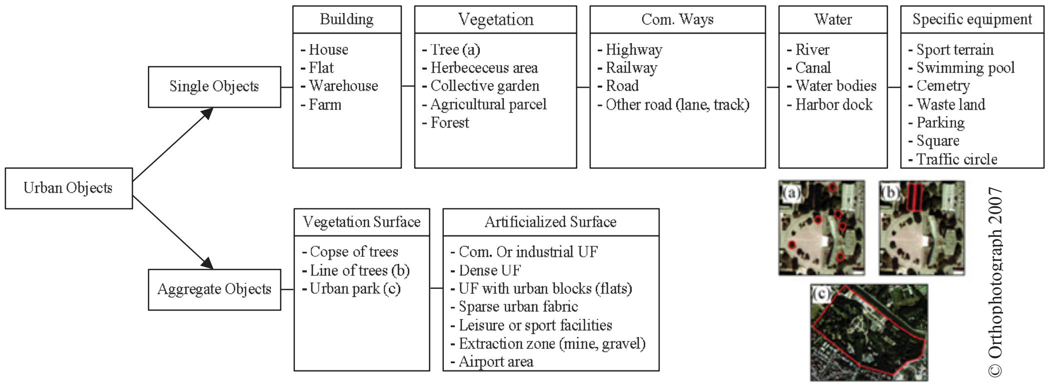

Figure 2: Examples of single and aggregate objects

In addition to intrinsic attributes – shape, texture, spectral features -; spatial relations among urban objects are depicted by means of topological attributes (Table 1). Qualitative values are assigned to all these indicators, e.g. long, medium and short to describe length; linear, square, circular and rectangular for shape.

This domain ontology was implemented with OWL 2.0 (Web Ontology Language)† under Protégé‡, from a dictionary of geographical objects specifically designed for image interpretation by expert geographers from the LIVE team of University of Strasbourg [22].

† http://www.w3.org/TR/owl2-overview/

Table 1: Spatial relationships among urban objects

Spatial relationship	Description
Adjacency	Objects that are adjacent to another object
Inclusion	An object A is included in another object B when A is within the bounds of B
Composition	Object constituted by other objects
Alignment	Organization of a set of objects (linear)
Distance	Distance between objects

According to the dictionary and as an example, a part of the definition of an "agricultural parcel" is presented following the Manchester OWL syntax.

```
Class: SimpleGeoObject
   SubClassOf: GeoObject
   ...
Class: Vegetation
   SubClassOf: SimpleGeoObject
   ...
Class: AgriculturalParcel
   SubClassOf: Vegetation
   EquivalentTo : (hasShape some
                      (Square
                       or Rectangle))
                  and (hasWidth some
                      (Large
                       or Medium))
                  and (hasLength some
                      (Large
                       or Medium))
                  and (hasSpectralSignature some Vegetal)
                  and (hasSurface some Large)
   ...
```

3.2. Rules layer

This layer is in charge of managing different types of rules in order to allow reasoning on the individuals contained in the knowledge layer of the domain ontology.

There exist three types of rules:

- rules for addressing the symbol anchoring problem, explained in section 3.2.1,
- rules for qualitative spatial reasoning, detailed in section 3.2.2,
- rules to express expert knowledge about the specific characteristics of the geographical regions.

Hitherto, our team has been working on the rules of the first two types. Rules of the third type address, for instance, situations like the following: houses in the south of France are more likely to have a swimming-pool in their backyard than houses in the north of France, meaning that not all the expert rules have to be launched together for a specific image. Hence, mechanisms for selecting the "regionalization" of the rules need to be developed to adjust the scope of the system according to the geographical area.

The rules in this layer are implemented in Semantic Web Rule Language (SWRL)[§] that combines sub-languages of the OWL (OWL-DL and OWL-Lite) with the Rule Markup Language. In our application, two major reasons led the choice of SWRL to represent the reasoning rules. Firstly, the advantages of SWRL are its formal model-theoretic semantics and the close association to OWL, thus it can easily integrate the OWL-based

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‡ http://protege.stanford.edu

§ http://www.w3.org/Submission/SWRL/

domain ontologies from the knowledge layer with the rules. Secondly, SWRL is a descriptive language independent from concrete rule languages implementation within inference engines, which gives the user freedom to select the inference platforms. JESS** (Java Expert System Shell) has been selected as the inference engine for three reasons: (1) it works seamlessly with Java and is well documented, (2) it supports forward chaining and, to some extent, backward chaining, and (3) the SWRLJESSTab†† plug-in - integrated with Protégé - supports the interaction between OWL/SWRL and the JESS rule engine in a user-driven manner.

3.2.1 Rules for addressing the symbol anchoring problem

In order to provide a general description of the objects in ontologies, their features are often expressed at a high level of abstraction, using qualitative values. For instance, Maillot and Thonnat [13] propose the "ontology of visual concepts", which defines concepts for texture, color, geometry, and topology relationships. The values of the attributes are linguistic variables such as "green", "rectangular", "adjacent to", "big", "homogeneous", "dark", etc. These generic qualitative values are necessary to provide a description of the objects independent from applications, although quantitative values are necessary to build concrete applications. This gap between qualitative and quantitative values is called *the symbol anchoring problem* [23].

Most of the existing systems in image recognition do not address the symbol anchoring problem. Therefore, the main goal of this type of rule is to tackle this problem. Indeed, the ontology has been developed with qualitative attributes, whereas the image analysis software throws quantitative values (length, surface, spectral signature, etc.). The rules serve to translate "raw" quantitative values coming from the image analysis software into qualitative values and thus to instantiate the ontology with new qualitative individuals, in order to launch the classification process afterwards. For instance, the shape of a region is calculated according to the value of several numerical indices obtained by the image analysis software:

- Morton index: Reports the ratio of the area of an entity to that of a circle of the same perimeter. Its value is 1 if the polygon is a circle, 0 if it is a degenerate line.
- Miller index: Index of spread which tends to 0 for a more stretched shape (1 if the shape is a circle)
- Gravelius index: Index of compactness. It is the inverse of Miller index; unbounded, its value is greater or equal to 1 (for a circle).

In the following example, the calculation of some qualitative values for the shape attribute from these numerical indices is achieved through two SWRL rules.

```
GeoObject(?s),
hasMiller(?s,?x),    swrlb:greaterThan(?x,0.84), swrlb:lessThan(?x,1.00),
hasMorton (?s, ?y),  swrlb:greaterThan(?y,0.73), swrlb:lessThan(?Y,1.00),
hasGravelius(?s, ?z),swrlb:greaterThan(?z,1.), swrlb:lessThan(?z,1.085),
                                                 -> hasShape(?s, "Circle")
GeoObject(?s),
hasMiller(?s,?x),    swrlb:greaterThan(?x,0.345), swrlb:lessThan(?x,0.78),
hasMorton (?s, ?y),  swrlb:greaterThan(?y,0.255), swrlb:lessThan(?y,0.63),
hasGravelius(?s, ?z),swrlb:greaterThan(?z,1.16), swrlb:lessThan(?z,2.50),
                                                 -> hasShape(?s, "Rectangle")
```

Some other rules included in our approach are those for calculating qualitative values for length, width, surface, elongation (mapping numerical values into the qualitative values `Large`, `Medium` or `Small`) and spectral signature (mapping numerical values of four spectral bands into qualitative values such as `Vegetation`, `Bare Soil`, `Mineral`, `Water`, etc.).

** http://herzberg.ca.sandia.gov/
†† http://protege.cim3.net/cgi-bin/wiki.pl?SWRLJessTab

3.2.2 Rules for qualitative spatial reasoning

Another important goal of the rules layer is to tackle spatial reasoning using well-known standards, such as the topological relationships RCC8 [24] or the CM8 primitives [25]. The interest in the CM8 primitives lies in the fact that they can be extracted directly by the image analysis software, in terms of the boundaries and contents of each segment. There exist rules that enable the use of RCC8 relationships from the CM8 primitives. These rules are also integrated in this layer to support qualitative spatial reasoning.

In this layer, a set of 94 SWRL rules was created to generate a composition table of RCC8 relationships and CM8 primitives, and their transitive closure. Note that the introduction of the CM8 primitives allows the factorization of some rules. For instance, in the initial RCC8 composition table, three rules state that, for three spatial objects `o1`, `o2`, `o3`, if `o1` is disconnected (`DC`) from `o2`, and `o3` is either identical (`EQ`) to `o2`, or a tangential (`TPPi`) or non-tangential (`NTPPi`) proper part of `o2`, then `o1` is disconnected from `o3`. As the CM8 primitive `Pi` (contains) is such that $\mathtt{Pi} \Leftrightarrow \mathtt{EQ} \vee \mathtt{NTPPi} \vee \mathtt{TPPi}$, then these three rules are factored into one single SWRL rule.

```
DC(?r1), Pi(?r2), RCC8(?r3), from(?r1,?o1), from(?r2,?o2),
from(?r3,?o1), to(?r1,?o2), to(?r2,?o3), to(?r3,?o3), -> DC(?r3)
```

It has to be remarked that the spatial relationships are reified due to their highly interdependent nature, since some relationships may be defined from others using the conjunction, disjunction or negation operators. Even though disjunction of roles is beyond the expressive power of OWL, reification offers a practical way out to this constraint.

3.3. Experience layer

This layer is intended to capitalize expert knowledge when, after segmentation, the system fails to classify a given region. Although this layer has not been developed yet, in the near future we will explore the feasibility of using a wide variety of methods for knowledge capitalization (CBR [26] or SOEKS and DDNA [27], [28]).

The main goal is to enrich the layer with new knowledge coming from domain experts and thereby, take advantage of their expertise for future classifications.

SOEKS and DDNA have been successfully tested in several diverse domains, mainly in engineering and medicine, e.g. for diagnosis of Alzheimer and breast cancer [17], [29] or IT projects management [30]. Nonetheless, there are no previous works on the joint use of CBR and DDNA. Within the framework of this project, the outcomes will then hold a proposition of a general architecture for the unified use of these technologies.

4. Experimental results

We hereby present our first results after applying this approach to tackle the symbol anchoring problem. We worked on an extract from a Quickbird (©DigitalGlobe) image of Strasbourg, France (Fig. 3), processed with the RegionMerging algorithm in order to obtain the corresponding segmentation (Fig. 4). Tables 2 and 3 present, respectively, the quantitative values for each region in the segmentation, calculated by the image analysis software developed by our team (Mustic[‡‡]), and the qualitative values obtained after applying the symbol anchoring from the rule layer.

Each row in Table 3 represents a new individual in the ontology (the last column should not be considered while creating them). The last column in the same table represents the final inference achieved for each individual in the classification, within the knowledge layer, using Protégé and the Hermit 1.3.6 reasoner.

‡‡ http://icube-bfo.unistra.fr/fr/index.php/Plateformes

Figure 3: Fields in the outer area of Strasbourg*

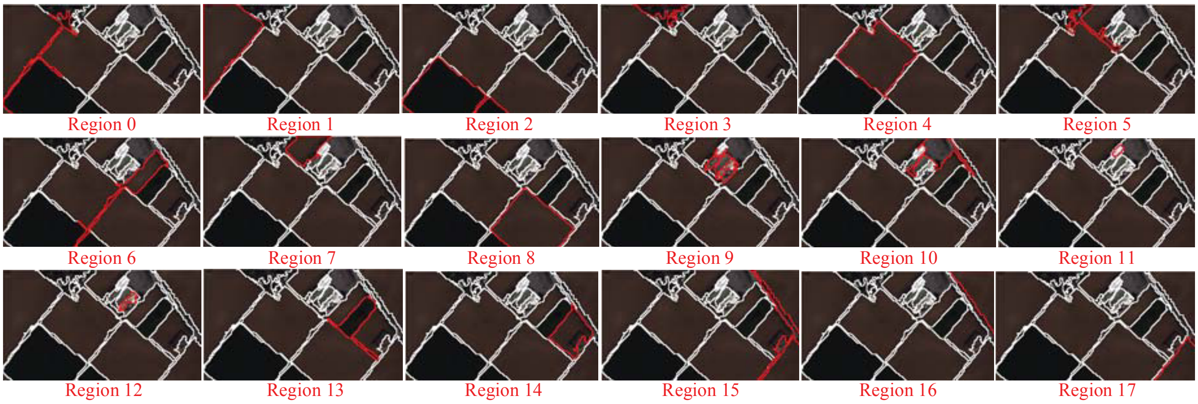

Figure 4: Segmentation of Fig. 3

Table 2: Quantitative values per region, obtained by the image analysis software

Region	Surf.	Length	Width	Elong.	Perim.	Miller	Morton	Gravelius	Solidity	SS_B1	SS_B2	SS_B3	SS_B4	SS_IBS	SS_NDVI
0	3192,00	97,50	32,74	2,98	256,52	0,61	0,43	1,28	1,00	214,84	74,09	54,10	79,28	78,69	189,01
1	452,00	108,59	4,16	26,09	385,69	0,04	0,05	5,12	0,13	184,73	93,55	157,65	123,62	149,76	48,71
2	3206,00	102,95	31,14	3,31	289,25	0,48	0,39	1,44	0,99	159,50	198,74	93,54	83,69	94,44	154,88
3	494,00	55,51	8,90	6,24	163,95	0,23	0,20	2,08	0,79	184,02	153,02	140,81	133,29	145,78	154,88
4	3118,00	63,45	49,14	1,29	247,13	0,64	0,62	1,25	0,92	212,33	71,67	40,49	89,24	77,04	207,57
5	419,00	53,07	7,90	6,72	223,19	0,11	0,19	3,08	0,34	178,92	106,87	143,15	130,37	147,04	65,17
6	877,00	129,61	6,77	19,15	320,83	0,11	0,07	3,06	0,37	209,51	80,28	107,93	113,00	122,74	154,88
7	745,00	44,25	16,84	2,63	125,16	0,60	0,48	1,29	0,90	211,43	82,30	83,44	91,80	100,71	154,88
8	3021,00	74,65	40,47	1,84	216,18	0,81	0,69	1,11	1,02	213,20	70,31	38,13	80,34	71,01	210,59
9	402,00	24,18	16,63	1,45	132,78	0,29	0,88	1,87	0,56	77,19	137,81	99,35	125,12	123,85	98,11
10	785,00	38,95	20,16	1,93	239,89	0,17	0,66	2,42	0,48	93,60	142,89	95,36	101,92	104,83	94,20
11	74,00	13,34	5,55	2,41	34,97	0,76	0,53	1,15	0,99	116,38	128,97	122,53	116,39	130,26	96,23
12	119,00	22,87	5,20	4,40	63,93	0,37	0,29	1,65	0,74	120,64	121,55	132,90	132,92	140,57	77,67
13	757,00	41,02	18,45	2,22	204,37	0,23	0,57	2,10	0,47	172,15	189,20	129,36	111,34	124,84	154,88
14	1071,00	41,03	26,10	1,57	160,48	0,52	0,81	1,38	0,85	203,96	71,84	121,42	80,44	117,02	154,88
15	571,00	57,92	9,86	5,87	313,81	0,07	0,22	3,70	0,20	167,51	106,03	132,94	128,37	140,07	88,85
16	1471,00	68,01	21,63	3,14	187,03	0,53	0,40	1,38	1,02	212,42	70,83	78,06	69,80	88,05	161,58
17	1006,00	47,22	21,30	2,22	143,22	0,62	0,57	1,27	0,97	207,74	57,28	143,92	55,47	121,26	154,88

So far, only a reduced series of tests have been performed. Aiming to verify the feasibility of our approach, the results of the classification of a small set of sample images have been compared to the ground truth given by an expert. In the framework of the Coclico ANR project[§§], which has funded this work and under whose context these experiments are included, a full set of images will be available and the use of a formal methodology for ontology evaluation purposes will be engaged.

[§§] Coclico ANR project number ANR-12-MONU-001

Table 3: Qualitative values per region and classification, obtained after application of the rules for symbol anchoring

Region	Spectral Signature	Shape	Surface	Length	Elongation	Width	Inference/Classification
0	Vegetation	Rectangle	Large	Medium	Medium	Medium	Garden/**AgriculturalParcel**
1	BareSoil	Linear	Medium	Large	Large	Small	**Path/**PublicPark
2	Vegetation	Rectangle	Large	Large	Large	Medium	Garden/**AgriculturalParcel**
3	Vegetation	Other	Medium	Large	Large	Small	**SetTrees**/ PublicPark
4	Vegetation	Rectangle	Large	Medium	Small	Medium	**AgriculturalParcel**
5	BareSoil	Linear	Medium	Medium	Large	Small	**Path**/ PublicPark
6	Vegetation	Linear	Medium	Large	Large	Small	AlignmentTrees/ PublicPark
7	Vegetation	Rectangle	Medium	Medium	Medium	Small	SetTrees/ PublicPark
8	Vegetation	Square	Large	Medium	Small	Medium	Garden/**AgriculturalParcel**
9	Mineral	Other	Medium	Small	Small	Small	PublicPark /BareSoil
10	Mineral	Other	Medium	Medium	Small	Small	PublicPark/BareSoil
11	Mineral	Other	Small	Small	Medium	Small	SmallParking/BareSoil
12	Mineral	Rectangle	Small	Small	Large	Small	SmallParking
13	Vegetation	Other	Medium	Medium	Medium	Small	**SetTrees**/PublicPark
14	Vegetation	Other	Large	Medium	Small	Small	Garden
15	BareSoil	Linear	Medium	Medium	Large	Small	**OtherRoad**/CollectiveBuilding
16	Vegetation	Other	Large	Medium	Large	Small	Garden/Lawn
17	Vegetation	Rectangle	Large	Medium	Medium	Small	ParkAgglom/AirportZone

Nine regions were correctly classified (regions 0, 1, 2, 3, 4, 5, 8, 13, 15, in bold the experts' classification). However, some results indicate that probably some concepts in the ontology are not seamlessly defined or the existence of segmentation problems in the image. Consider e.g. regions 7 and 14, they should have been classified as agricultural parcels, but the definition of the concept clearly entails certain inaccuracies, mainly regarding the area and shape attributes. Region 16 should be an agricultural parcel as well. However, as this region lies in the border of the image, its shape is not complete and therefore it is neither a square nor a rectangle. Finally, for a few regions such as 6, 9, 10, 11, 12, the inference is clearly incorrect due to segmentation problems; and for others such as region 17, the definitions of the concepts lack precision and lead to ambiguous or incorrect results.

Spatial reasoning is out of the scope of this example. Nonetheless, since the image analysis software returns, for every region, a list of its adjacent regions, this information could also be exploited to adjust the classification results and improve its efficiency.

5. Conclusions

This article has presented our proposal and first results on the use of a semantic three-layered architecture to gradually face the automation of remote sensing image qualitative analysis. Despite the identified problems, the results are encouraging, as they show the feasibility of the proposed approach.

The semantic gap problem is addressed through the development of a domain ontology in the knowledge layer, whereas the symbol anchoring problem is tackled by means of the rules layer. The latter also supports qualitative spatial reasoning and the addition of rules to handle specific expert knowledge, e.g. to describe characteristic features of a particular geographic area. Finally, the experience layer will allow the capitalization of new expert knowledge when the inference thrown by the first two layers is not satisfactory.

The implementation is currently carried out basing on OWL-DL over a single image. Nevertheless, further aspects to take into account include the use of fuzzy extensions of DL to cope with imprecise data coming from the low-level image processing methods, or the modeling of statistical knowledge about object relationships with probabilistic DL-rules.

Another improvement we are considering is the inclusion of temporal reasoning on a series of images. Hence, changes in regions over time would be detected, such as alterations in the physiognomy of landscapes or the spreading of cities.

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