International Journal of Knowledge-based and Intelligent Engineering Systems 17 (2013) 55–65
DOI 10.3233/KES-130264
IOS Press

From expert knowledge to formal ontologies for semantic interpretation of the urban environment from satellite images

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Abstract. The widespread introduction of satellite imagery with several spatial, spectral and temporal resolutions is a real opportunity to analyze and characterize the urban environment. These last few years, the Object-Based Image Analysis (OBIA) approach has been largely developed and applied for urban applications. However, a major issue in this approach is domain knowledge formalization and exploitation. In this paper, after a detailed presentation of related works in the domain of semantic interpretation using ontologies, a taxonomy of urban objects and a framework to describe urban objects and their spatial organization is presented. This taxonomy is then formalized in a domain ontology using the semantic web ontology language and rules (OWL and SWRL).

Keywords: Urban environment, satellite imagery, ontology, semantic interpretation, OWL, SWRL

1. Introduction

The late years of the last decade marked a turnover for typical ground resolutions, from around ten meters to one meter for images acquired from optical sensors. When complex environments, such as urban areas, are concerned, this evolution means more than just more visibility of details: it implies a change of approach to the problem of information extraction, both in terms of goals and techniques [1]. With the very high spatial resolution of images, it makes sense to turn the attention from general, extensive inspection of urban areas (e.g., land cover and urban sprawl or the study of the density of buildings) to more intensive extraction of specific features, such as individual building. In the domain of image interpretation of these images, differences are observed between the visual interpretation of the spectral information and the semantic interpretation of the pixels, mainly due to different levels of abstraction [2]. The semantics is not always explicitly contained in the image and depends on domain knowledge and on the context. This problem is known as the semantic gap [3] and is defined as the lack of concordance between low-level information (i.e. automatically extracted from the images) and high-level information (i.e. analyzed by urban experts). In order to reduce the semantic gap, the OBIA (Object-Based Image Analysis) approaches, that are based on the use of domain knowledge, have been developed [4, 5]. These methods involve the segmentation of the images into homogeneous regions and the characterization of objects with a set of spectral (signature, index), spatial (shape) and topological (adjacency, inclusion) features. Only few works have focused on the use of domain knowledge for classifying urban objects [6], and a major issue in these approaches is therefore domain knowledge formalization and exploitation.

Building an urban ontology is a difficult task because, most of the time, the knowledge to include is implicit and is held by the domain experts [2]. However,

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ISSN 1327-2314/13/$27.50

in the domain of image interpretation, experts use different visual or qualitative keys of interpretation based on both the intrinsic characteristics of objects (size, shape, texture of a house, for instance) and their spatial organization [7].

In this context, the aim of this paper is to highlight the benefits of building a thematic ontology whose concepts are extracted from a dictionary of urban objects and are specifically designed for image interpretation. The formalization of the geographic knowledge was therefore achieved with a logical based ontology language with specific guidelines to ensure that reasoning within this ontology will effectively assist the urban object recognition process.

In this paper, we first present approaches using ontologies for geographical analysis or for image interpretation (Section 2). Secondly, we present the conceptualization of the domain knowledge, made by expert geographers in the form of a dictionary of urban objects (Section 3). Thirdly, we present the design principles of our ontology and its implementation in OWL 2.0 (Ontology Web Language [8]), and SWRL (Semantic Web Rule Language) [9] (Section 4). Fourthly, we present some results which highlight the reasoning schemes of the ontology (Section 5). We finally conclude with some perspectives of future work (Section 6).

2. From expert knowledge to ontologies: State of the art in image recognition

2.1. *Ontologies for image analysis*

An important issue in the domain of image recognition is that an image is inherently ambiguous, because its content does not carry intrinsic information which allows to make the distinction between what is relevant and what is not. This implies that the interpretation of the input images depends on the goal that is pursued, and that explicit knowledge must be formulated in order to provide an adequate interpretation of the image semantics in a given context. For instance, the search of vegetation in the image strongly depends on the season (red in autumn, green in spring).

In OBIA approaches, image classes can either be defined by extension or by intension [9]:

- In the definition *by extension*, the information is represented by samples, who represent a region extracted from the image which delineates the object of interest.
- In the definition *by intension*, the information is represented by a linguistic description, which consists in a high-level description, often implemented by an ontology.

The term "ontology" is borrowed from philosophy and is concerned with the study of the nature and the relations of "being". In the context of computer systems, what "exists" is what can be represented. Gruber defines an ontology as "an explicit specification of a conceptualization" [11].

An ontology describes, then, the concepts and relationships in the modelled field for the purpose of enabling knowledge sharing and reuse [12]. Since the end of the nineties, many works on image analysis tried to benefit from ontologies.

Some of these ontologies are oriented mostly towards the modelling of satellite images features and the associated analysis techniques [13]. Others focus on specific domain knowledge representation, for example [14,15] in the urban domain. General frameworks have been designed in order to embed these specific domain ontologies within more generic geographic ontologies [16] or to merge multiple ontologies [17]. Finally, bridging the so-called "semantic gap" is the focus of many ontology based researches [18,19].

Despite of the fact that all these projects are based on ontologies, domain ontologies are scarcely used to effectively guide image analysis. Instead, they often describe in detail metadata about the representation or the hierarchy of concepts but often ignore an important question: can the modelled knowledge be used in remote sensing image interpretation?

2.2. *Dealing with the symbol anchoring problem in ontologies*

In order to provide a general description of the objects in ontologies, their characteristics are often expressed at a high level of abstraction, using qualitative values. For instance, [20] propose the "ontology of visual concepts" that defines the concepts of texture, colour, 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 that is independent of the applications. But *quantitative* values are necessary to build concrete applications. This gap between qualitative and quantitative values is called the *symbol anchoring problem* [21]. To address this problem and connect the linguistic symbols to numerical image data, it is possible to define symbol grounding dictionaries, such as the “Colour Naming System” [22], where each term is assigned to a predefined range of numerical values.

Most of the existing systems in image recognition do not address the *symbol anchoring problem*. Our research team developed an image analysis system where the concepts, representing urban objects, are organised hierarchically and are characterized by attributes that can be directly calculated from the image segmentation (reflectance, spectral index, shape, or texture) [2]. This system, which addresses the symbol anchoring problem, needs to be improved to deal with problems such as over-segmentation (e.g. shadows of houses that are considered as separated objects) or under-segmentation (e.g. neighbouring houses that are clustered and considered as a single building).

One of the main goals of the work presented in this paper is to provide a conceptual framework that improves the existing software by representing, in a more expressive way, the relations between concepts (not only the hierarchy, but also other types of relationships). The use of better structured domain knowledge and of the reasoning capabilities of the ontology can enhance the image interpretation process.

3. Knowledge acquisition and conceptualisation of the urban environment

3.1. Knowledge acquisition

Methodologies identify knowledge acquisition as an important and independent step for ontology development [23]. We reviewed the geographical literature for defining typologies of objects in an urban context based on visual interpretation from aerial photographs or satellite imagery. The proposed nomenclature is based on urban objects defined in urban GIS (Geographic Information System) platforms used to characterize western cities. At the first level, an urban area is composed of five categories of *elementary objects*. Each category is composed of urban elements called *single* objects because they correspond to the most basic element of the urban space (that cannot be decomposed). The spatial organization of single objects allows the definition of several settlements or urban fabrics called here *aggregate* objects (Fig. 1).

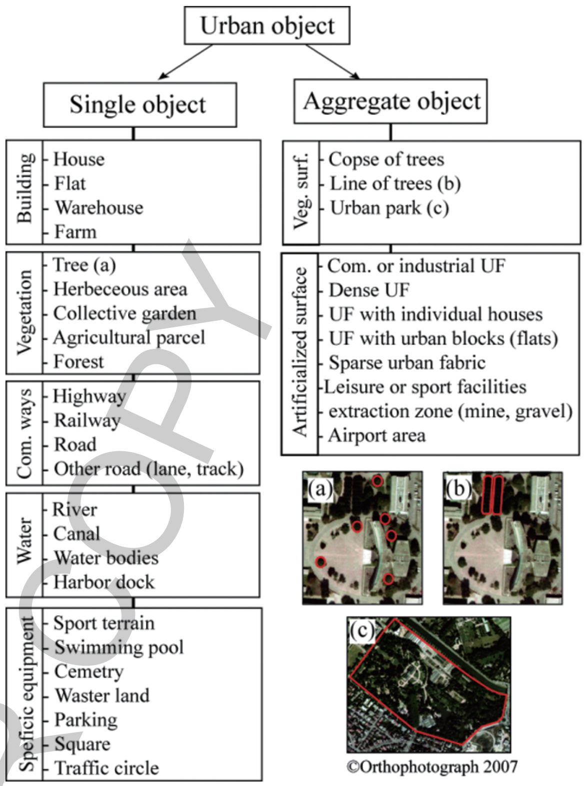


Fig. 1. List of *single* and *aggregate* objects in the dictionary. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

3.2. Conceptualization in a dictionary

Conceptualization refers to organizing and structuring the knowledge acquired during the specification phase in a semi-formal way, using a set of representations that both domain experts and knowledge engineers can understand [24]. All the concepts are stored in a dictionary with:

– A common textual definition of the objects (accepted by the user communities in urban planning and management) for three ranges of spatial resolution;
– The range of spatial resolution at which single and aggregate objects are identifiable;
– A qualitative description of the characteristics of each object: size (length, width), elongation, shape, texture, context, and spatial relationships.

Three ranges of spatial resolution (THR: [0.5 m–5 m], HR1: [5 m–15 m] and HR2:]15 m–30 m]) [25] have been used because some concepts only exist at a single spatial resolution (for instance, it is difficult to identify a tree on a 20 m spatial resolution image)

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

Fig. 2. Spatial relationships used by expert in visual interpretation.

while other concepts exist at all spatial resolution (for instance, a lake can be identified in images where the spatial resolution ranges from 30 to 1 m). Regarding the spatial relationships, five classical relations used in GISs have been selected (Fig. 2). For each indicator, qualitative values (e.g. big, medium, small for the length) and textual information (e.g. rectangular, square, circular for describing the shape of an object) are given in order to be independent of the OBIA approaches where quantitative values will be calculated from the segmentation step.

4. Design principles of the ontology

The hierarchy of concepts has been modelled according to the dictionary of geographical objects presented in the previous section. Figure 3 shows a partial view of the corresponding class hierarchy using the Protégé [24] editor.

4.1. Addressing the symbol anchoring problem

Our ontology is based on qualitative values as seen in the previous section. In OBIA approaches, satellite images are segmented into homogeneous regions which are characterized by a set of spectral, spatial and topological features. To solve the symbol anchoring problem (Section 2) and reduce the gap between qualitative and quantitative values, we propose the image analysis framework detailed in Fig. 4. Our proposition is to use the general notion of embedding, borrowed from topology. Satellite images with various resolutions are first segmented. The obtained regions constitute the concrete objects of Fig. 4. The set of indicators presented in Section 3.2 is then calculated by the image processing system, and the obtained numerical values are associated to the attributes of the concrete objects.

The mapping from quantitative to qualitative values depends on the category of the abstract object. For example, a thousand squared meters area is a big building, but it is a very small forest. Currently, only a simplified embedding is implemented in our system:

- The correspondence between concrete and abstract objects is one to one. Actually, only one instance is created in the ontology for each obtained region. This instance is associated with both qualitative and quantitative values.
- Quantitative attributes are defined as OWL *data properties*, and qualitative attributes are defined as OWL *object properties*.
- The mapping from quantitative to qualitative values is realized through SWRL rules. For example, we may relate the quantitative hasNumSurface data property (numerical value ?ns) with the qualitative hasQualSurface object property (qualitative value ?s) for *Building* and for *Forest* with the following rules:
  * Building(?x), hasNumSurface(?x, ?ns), greaterThan(?ns, 500, hasQualSurface(?x, ?s) -> Big(?s)
  * This rule means that if a building has a surface greater than $500m^2$, it is a big building.
  * Forest(?x), hasNumSurface(?x, ?ns), lessThan(?ns, 10000), hasQualSurface(?x, ?s) -> Small(?s)
  * This rule means that if a forest has a surface smaller than $10000\ m^2$, it is a small forest.

4.2. Reification of relationships

In addition to the intrinsic characteristics of urban objects, the ontology also allows the automatic management of a certain number of restrictions or rules about the possible (or impossible) relationships between an object of type X and an object of type Y. These spatial relationships include information about adjacency, inclusion, or proximity among objects.

Although spatial relationships seem to be simple binary relations, they often require additional attributes. Actually, in order to associate a value to a spatial relation between two objects, reification is necessary. Reification is widely used in conceptual modelling: it consists in converting a relationship into an entity. We show below the case of the "distance" relationship and of the topological relationships.

4.2.1. The distance relationship

OWL-DL properties are binary relations and this entails the impossibility of representing the Distance relationship, because its value is a property of the relationship itself and not of the individuals that participate in the relationship. In order to solve this problem it is proposed to reify the relationship.

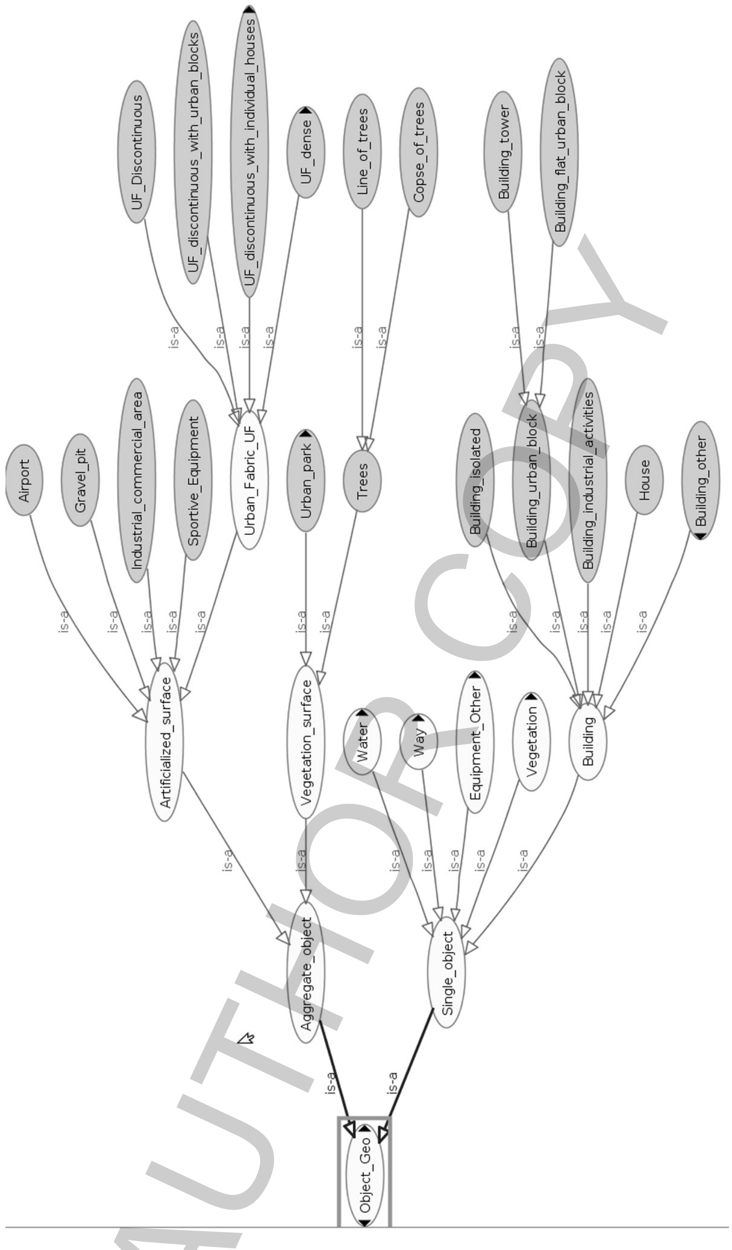


Fig. 3. Partial hierarchy of the concepts in the ontology.

Therefore, besides the Distance class (Fig. 5), it is needed to create a Qualitative Values class for the possible values of the distance.

The object properties called to and from link the SpatialObject class to the Distance class, then the *value* object property relates the Distance class to the class of Qualitative_Values. This collection of classes and object properties emulates a weighted relationship between two objects, where the weight is the value of the distance between both of them.

4.2.2. Topological relationships

The qualitative spatial reasoning framework based on the RCC (Region Connection Calculus) theory [27] is used in our ontology. The interest of reifying these topological relationships, is to define a set of hierarchical concepts, which represent, not only the RCC relationships, but also the intermediate concepts corresponding to the conjunction, disjunction or negation of RCC relationships. We will show below how these reified intermediate concepts are used to implement the

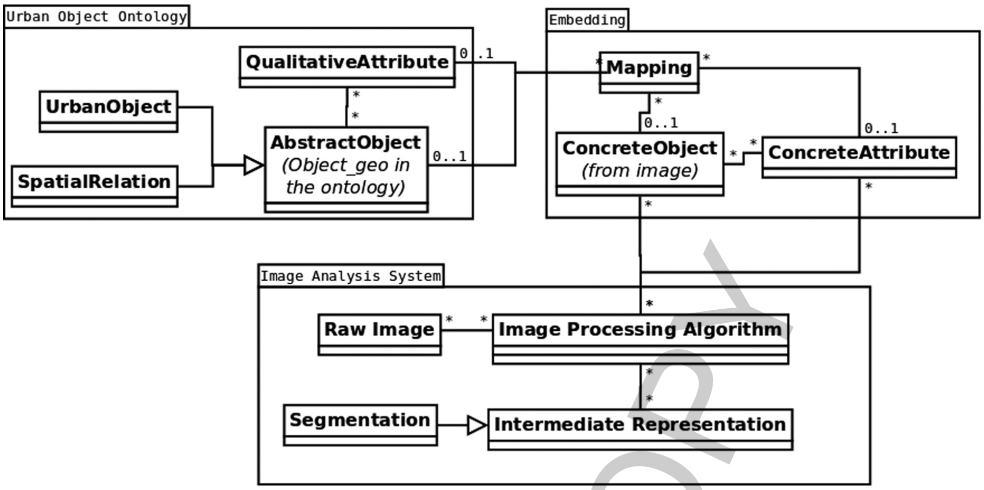


Fig. 4. General framework for the mapping between concrete and abstract objects.

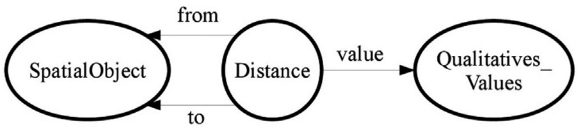


Fig. 5. Reification of the distance relationship.

rules of composition in OWL.

For instance, Fig. 6 shows the hierarchy of concepts for the simplified RCC5 system, that defines five disjoint basic spatial relationships: EQ (equal), PO (partial overlapping), DR (discrete), PP (proper part), and PPi (proper part inverse).

The reification of a topological relationship R(x,y) between two regions x and y is represented by the following clause: from(R,x) $\wedge$ to(R,y), where R is the concept representing the topological relationship R, and "from" and "to" are the predicates – represented by OWL's 'object properties' – which allow to link the region x to the region y, through the object R.

The rules of composition of topological relations are used to infer the possible relations between two regions x and z, given the known relations between the regions x and y on the one hand, and between y and z on the other hand [28]. For instance, the following composition rule:

$$\mathrm{DR(x,y)} \wedge \mathrm{PO(y,z)} \text{ -> } \mathrm{DR(x,z)} \vee \mathrm{PO(x,z)} \vee \mathrm{PP(x,z)}$$

is expanded after reification as follows (we show here the SWRL syntax):

DR(?r1),from(?r1,?x),to(?r1,?y),

PO(?r2),from(?r2,?y),to(?r2,?z),

from(?r3,?x),to(?r3,?z) -> DR_PO_PP(?r3).

In this formula, DR_PO_PP is an intermediate concept defined as the disjunction of DR, PO and PP. We can notice that this concept is already included in the above hierarchy of RCC5 concepts.

This is a major interest of reification in our approach, because, otherwise, such a disjunction of predicates would not be possible to represent in the conclusion of a Horn clause, and consequently would not be implementable by means of a SWRL rule.

5. Image interpretation with the ontology

In the previous sections, we presented the design methodology and the ontology. We will now outline its use during the interpretation of satellite images. While the description of the ontology was made at the conceptual level, image interpretation will involve individuals. The image analysis modules must provide a segmentation of the image. A segment is a contiguous set of pixels with high homogeneity. For each segment detected in the image, an instance will be created in the ontology. Standard OWL inference mechanisms can then be used to classify the instances according to their characteristics and their relationships.

The problem of the semantic labelling of the image content has been discussed in [2]. The work presented in this paper focuses on the inferences allowed in the ontology after an incomplete semantic labelling has been done.

For testing the ontology, some examples of instances have been hand made in Protégé 4.2 beta [24], with the embedded Hermit 1.3.6 reasoner [29].

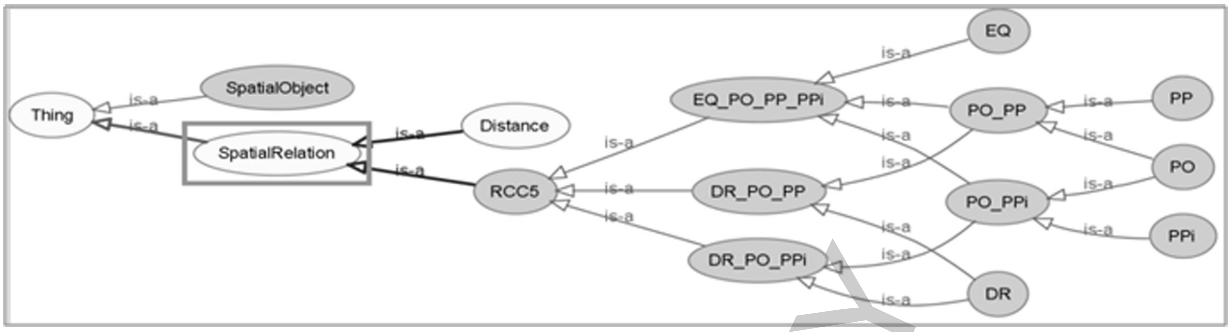
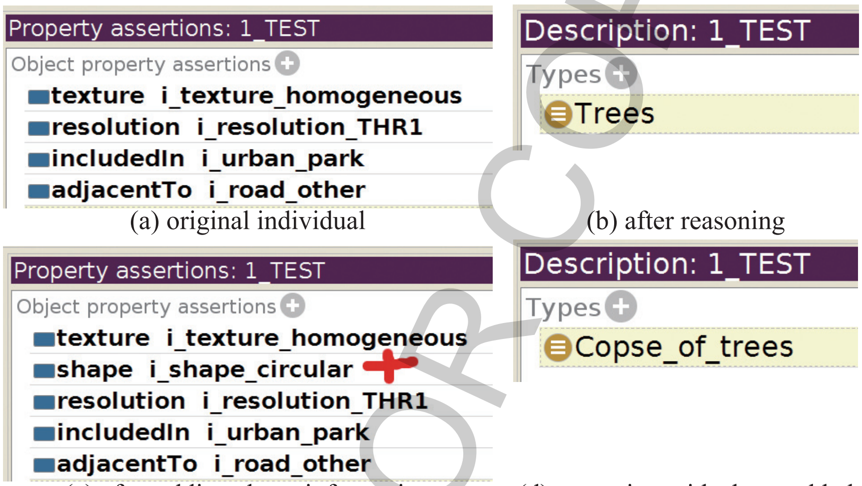


Fig. 6. The hierarchy of concepts for RCC5 in Protégé.



(a) original individual (b) after reasoning

(c) after adding shape information (d) reasoning with shape added

Fig. 7. Definition and inferences for the 1_TEST individual. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

5.1. *Classifying objects according to their characteristics*

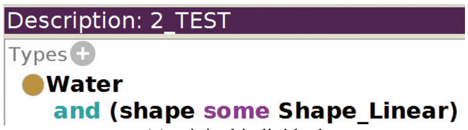
Let us suppose that after analyzing the data provided by an unknown geographic object called 1_TEST, the following information can be asserted (Fig. 7(a)):

- It is adjacent to an object Road_other.
- It has a Heterogeneous texture.
- It is included in an Urban_park.
- The resolution at which the object was observed is THR1.
- It is observed an *Alignment* among the objects that compose it.

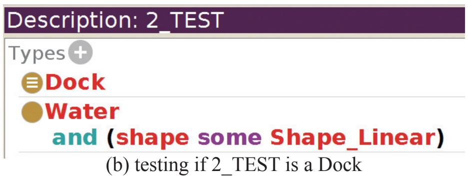
To test the class membership of 1_TEST the above information is expressed as restrictions in OWL-DL. After execution of the Hermit reasoner in Protégé, the results show (Fig. 7(b)) that the reasoner inferred that 1_TEST belongs to the class Trees. In the ontology, Trees has two subclasses Copse_of_trees and Line_of_trees. These two subclasses have more specific characteristics that allow to distinguish between both of them. The definition of Trees contains the common characteristics of Copse_of_trees and of Line_of_trees.

The properties of 1_TEST satisfy these common characteristics. Therefore, if the class Trees had not been created, 1_TEST would not have been classified neither as Copse_of_trees nor as Line_of_trees because all the properties in these subclasses are not satisfied by the individual. In this case, the classification would have taken place at higher levels of the hierarchy, wasting valuable information. Therefore, creating super-classes for classes with common restrictions helps in discriminating the similar subclasses during classification.

Suppose now that it is asserted that the individual 1_TEST has a circular shape (Fig. 7(c)). The reasoner



(a) original individual



(b) testing if 2_TEST is a Dock

Fig. 8. Definition and inferences for the 2_TEST individual. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

can now distinguish between the subclasses of Trees and infer that the individual 1_TEST is a member of the Copse_of_trees class (Fig. 7(d)). This occurs because the individual satisfies the restrictions of Trees and also satisfies the restrictions of the subclass.

Next example concerns a new individual 2_TEST. The only clear information that can be asserted is that it is made of water and has a linear shape (Fig. 8(a)). It is not possible to prove the membership of the individual to any of the subclasses of the Water class due to the lack of restrictions on it. It is possible, however, to check the sub-classes to which the individual cannot be a member of, because, if at least one of the restrictions on the individual contradicts the definition of one of the sub-classes in *Water*, an inconsistency will take place.

For example, to test the membership of 2_TEST to Dock, this class is added to the definition of the individual (Fig. 8(b)).

The execution of the reasoner at this stage indicates that an inconsistency has been made (indicated by the red colour in Protégé). Therefore, it can be concluded that 2_TEST is not member of Dock. In fact, the definition of this class indicates that its shape is rectangular, contradicting, therefore, the assertion of the linear shape made on the individual.

Notice that if this class would not have made the ontology inconsistent, it would not have been possible to state that the individual is, actually, a member of the Dock class. This would only have stated that the individual satisfies some of the restrictions of it, but the information is insufficient to assert that it is member. Therefore, when the information is not sufficient to state the membership of an individual to a certain class, this procedure can be followed by testing the non-membership of the individual to any of the subclasses of the initial one.

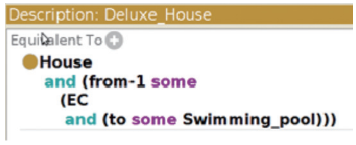


Fig. 9. Definition of a Deluxe_house in Protégé. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

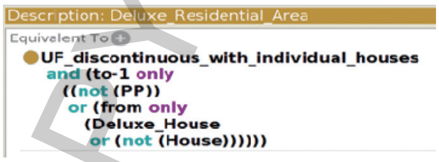


Fig. 10. Definition of a Deluxe_Residential_Area in Protégé. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

5.2. *Reasoning on image objects and their spatial relationships*

In this section, we define two concepts to illustrate the use of topological relationships to characterize the objects of the image: a Deluxe_Residential_Area is an area containing only houses of the class Deluxe_house, which are houses with a swimming-pool. Figures 9 and 10 show the definition of these two concepts in Protégé.

Let us note that the spatial relationship EC (Externally Connected), that is a topological relationship of the RCC8 set, is a sub-concept of the relationship DR (Discrete) of the RCC5 set (see Section 1.6), and means "adjacent to". Similarly, the relationship PP (Proper Part) of RCC5 means "included in", and its inverse PPi means "contains".

In the area of Fig. 11,[1] the image segmentation software has found five elementary objects: H1, H2 and H3, which have been recognized as houses, and SP1 and SP2, which have been recognized as swimming-pools.

In order to illustrate the reasoning mechanisms of OWL-DL, we first consider that the area A1 is an aggregate object containing only the houses H1 and H2, and their adjacent swimming-pools, SP1 and SP2 (see Fig. 12).

Any sound OWL reasoner will not recognize A1 as an instance of Deluxe_Residential_Area. This neg-

[1]East of Strasbourg area: subset of a Quickbird image (MS with four spectral bands), Digital Globe 2008. This image is the property of LIVE, University of Strasbourg, UMR 7362.

Fig. 11. Houses in the outer area of Strasbourg and the resulting segmentation. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

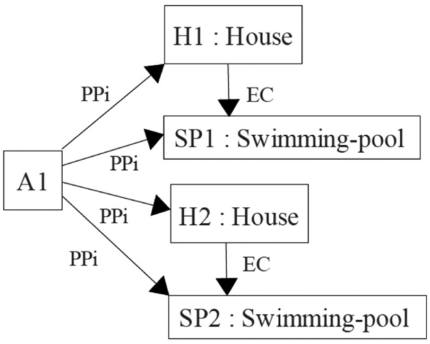


Fig. 12. Topological relationships between the instances computed from the image.

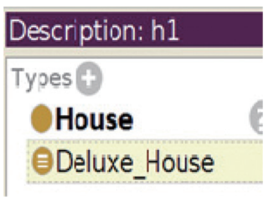


Fig. 13. The Protégé reasoner infers that H1 is a Deluxe_house. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

ative result would be surprising if working with an object oriented database, but it is consistent with the OWL-DL semantics which is based on the open world assumption.

Actually, the OWL-DL reasoner infers that H1 and H2 are instances of Deluxe_house (see Fig. 13), because they are respectively adjacent to swimming-pools SP1 and SP2. But with the open world assumption, the existence of another house H3 cannot be excluded. Consequently, if we postulate that H3 was not a Deluxe_house and that A1 contained H3, then A1 would not be a Deluxe_Residential_Area.

Therefore, universal quantifiers applied to multi-valued properties, seem to preclude the effective use of the ontology for instance recognition. Fortunately, the

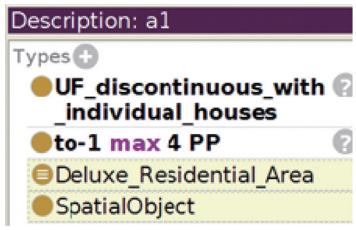


Fig. 14. Cardinality constraint in Protégé stating that a maximum four objects is included in A1. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

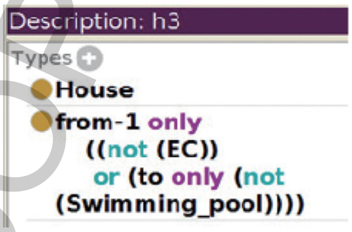


Fig. 15. H3 is defined in Protégé as a House which is not adjacent to a Swimming_pool. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

OWL-DL cardinality restrictions, when they are applied to the instances extracted from the image, allow to avoid, if necessary, the creation of implicit instances and relationships.

In our example, the image recognition software must state that the houses H1 and H2 and the swimming-pools SP1 and SP2 are the only objects included in A1. In this case, the A1 instance description must be extended with this knowledge by a cardinality constraint, which is written as shown in Fig. 14 (to-1 max 4 PP means that the urban area A1 contains at most 4 objects).

After this specification, the Protégé reasoner infers that A1 is a Deluxe_Residential_Area (Fig. 14).

If we consider now that the area A1 contains also the house H3 that is not adjacent to a swimming-pool, then the OWL-DL reasoner infers that A1 is not a Deluxe_Residential_Area (see Fig. 16: when the reasoner generates an inconsistency, the contradictory concepts are annotated in red). This inference is only made possible if it is explicitly stated that H3 is not adjacent to a swimming-pool (see Fig. 15: from-1 only ((not (EC)) or (to only (not (Swimming_pool))) means that if the house H3 is adjacent to an object, then this object is everything but a swimming-pool).

We have shown in this section that our ontology allows to define new high-level concepts which are described by means of topological relationships existing

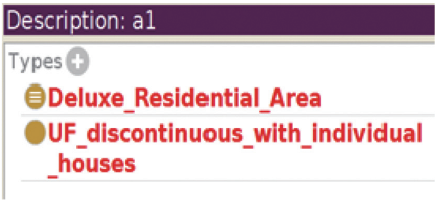


Fig. 16. The Protégé reasoner generates an inconsistency if it is asserted that A1 is a Deluxe_Residential_Area. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/KES-130264)

between lower-level concepts. Then the OWL-DL inference mechanisms integrated in the ontology provide a consistent framework for reasoning about these concepts.

6. Conclusion and perspectives of future work

In this paper, we propose to improve an original framework for image recognition firstly detailed in [2]. These improvements mainly concern the ontology design. More precisely, some qualitative information has been added both to the intrinsic characteristics of the urban objects and to the relationships between them. Indeed, although the proposed ontology attempts to resolve the symbol anchoring problem, the use of qualitative values makes this tool useful for helping urban experts to identify objects when numerical values are not present.

We have seen that the first goal of our ontology is not to provide a common vocabulary or interoperability facilities between existing geographical systems [30], as is the case in most of the current approaches, but to provide a reasoning tool based on a semantic model of the urban objects, in order to help automatic image interpretation.

Moreover, the formalization of the image analysis domain knowledge by means of a model based on a logic theory allows for consistency checking. This consequently allows to make assertions that are usually implicit in the semantics of the image and that conventional methods cannot easily infer.

The preliminary results of this project demonstrate the effectiveness of the model for identifying objects based in their spatial properties. There are some unexpected assertions, nevertheless. Since the model was built from a dictionary of urban objects, every assertion is based on the information that can be found in the dictionary, implicitly or not. If the results do not correspond to those expected, then some adjustments in the dictionary are needed.

The use of OWL as ontology language made possible to reason on the model. Another aspect that was essential to the development of this project in OWL was Protégé. Its friendly syntax for writing OWL restrictions as well as the embedded reasoners and the tools that provide for checking and explaining inconsistent ontologies have eased the building and testing of our model.

This work also offers some interesting perspectives. The mapping between abstract and concrete objects showed in section 4.1 is a first step, but future work includes the creation of a new ontology representing the ranges of numerical values associated to the objects in the ontology.

The need to represent cases where an object can be a member of several classes with different probabilities, introduces an uncertainty. An approach based on probabilistic ontologies should be used. Some extensions that enable probabilistic reasoning in OWL, such as PRONTO [31] or PR-OWL [32], deserve to be studied.

We are also working with experts in text mining, in order to create automatically the domain ontology from the textual description of the geographic concepts. This work will allow the verification of the current version of the ontology and will facilitate further developments.

Finally, the definition of rules based on the spatial relationships among urban objects could also allow correcting a possible erroneous interpretation of the image (e.g. due to the over-segmentation of it), by comparing the same portions of the image at different resolutions. In this way, a classification strategy based on the multi-resolution analysis of spatial relationships could be integrated in our system to improve the whole process.

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