A Fuzzy-Rule Based Ontology for Urban Object Recognition

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Abstract: In this paper we outline the principles of a methodology for semi-automatic recognition of urban objects from satellite images. The methodology aims to provide a framework for bridging the semantic gap problem. Its principle consists in linking abstract geographical domain concepts with image segments, by the means of ontologies use. The imprecision of image data and of qualitative rules formulated by experts geographers are handled by fuzzy logic mechanisms. We have defined fuzzy rules, implemented in SWRL (Semantic Web Rule Language), which allow classification of image segments in the ontology. We propose some fuzzy classification strategies, which are compared and evaluated through an experimentation performed on a VHR image of Strasbourg region.

1 INTRODUCTION

In the domain of knowledge representation for image recognition, we outline the principles of a methodology for semi-automatic extraction of urban objects from Very High Resolution (VHR) satellite images. This methodology relies on the design and implementation of ontologies, which are an effective tool for domain's knowledge formalization and exploitation (Gruber, 1993) and for the implementation of reasoning. We have defined two ontologies, the domain ontology and the image ontology. The domain ontology (Cravero et al., 2012) describes urban objects at high level of abstraction (houses, roads, vegetation, rivers, etc.). The image ontology describes the image itself, and its components (image objects), which are assemblies of segments resulting from the image segmentation process. The ontologies are implemented in OWL2 (Ontology Web Language) under the Protégé-OWL2 editor (Grau et al., 2008).

The aim of our approach is to propose an ontology-based framework for addressing the semantic gap problem (Smeulders et al., 2000), which characterizes the lack of concordance between the semantic interpretation of image objects, and the pixel numerical values describing them. Actually, ontologies have been widely used in the context of image recognition. We give here a brief overview of some significant work in this domain. (Maillot and Thonnat, 2008) proposed an ontology-based object learning and recognition system involving different aspects of cognitive vision. Their approach relies on an ontology of visual concepts, such as colour and texture, which can be seen as an intermediate layer between domain knowledge and image processing procedures. However, this kind of learning system requires that the expert produces examples for each of the concepts he is looking for.(Athanasiadis et al., 2007) present a framework for both image segmentation and object labeling using an ontology in the domain of multimedia analysis. In the field of remote sensing, (Fonseca et al., 2002) propose the construction of ontologies at different levels of Geographic Information System (GIS). The ontologies are seen as components, cooperating to fulfill the system's objectives. Indeed, in GIS's conception, multiple ontologies are commonly used to represent different levels of knowledge, but this leads to complex systems which are difficult to understand as a whole. (Forestier et al., 2012) pointed that although ontologies are useful to describe hierarchies of concepts and meta-data about image representation, they often fail to propose an operable representation of the knowledge that can be effectively used for image interpretation in the domain of remote sensing. They proposed a solution, based on the construction of a knowledge base, that can be considered as a starting point for our approach, in the sense we propose to use the ontologies in an applicative way, in order to provide a semantic labelisation of the data extracted from the image. The implemented ontologies have the goal to help to automatically link image objects (characterized by quantitative values) with domain objects (characterized by qualitative values). The problem of mapping between qualitative and quantitative values is called the symbol anchoring problem (Coradeschi and Saffiotti, 2003).

Our approach also copes to the imprecision of data due to different types of sensors, sampling of data, etc. The use of fuzzy logic allows to take this imprecision into account and also facilitates the translation of expert's rules which are usually qualitatively formulated in natural language. Our methodology is based on a multi-level analysis, and implements fuzzy rules for the classification of the image segments in the ontology. These rules are written with SWRL (Semantic Web Rule Language) (Horrocks et al., 2004). The originality of our approach lies in the fact that, despite the popularity of fuzzy logic, few works integrate in the ontologies a fuzzy reasoning in the context of real world applications (Ghorbel et al., 2010), and particularly in the domain of urban object recognition (Belgiu et al., 2013).

This paper is organized as follows: in section 2, we show an overview of the proposed ontologies. In section 3, we outline the principles of a multi-level methodological framework, which uses fuzzy rules for the classification of urban objects in the ontology. In section 4, we present a partial implementation of the methodology, which is illustrated by an experimental evaluation of the image segments fuzzy classification, based on their spectral properties. This experimentation is performed on a VHR urban image of Strasbourg city. We finally conclude in section 5.

2 ONTOLOGIES OVERVIEW

Ontologies are a natural way to express a hierarchy of concepts and their properties. They incorporate reasoning mechanisms, which allow the classification of individuals in the most appropriate class. We present here two ontologies -domain and image ontologies- that we have implemented to assist the task of semi-automatic urban object recognition.

2.1 The domain ontology

This ontology has been defined in collaboration with experts geographers who created a dictionary of urban objects (de Bertrand de Beuvron et al., 2013).

At the higher level of the hierarchy, the objects can be either (see figure 1):

- single objects, which belong to elementary classes (building, vegetation, etc.)
- aggregate objects, which are composed of single objects.

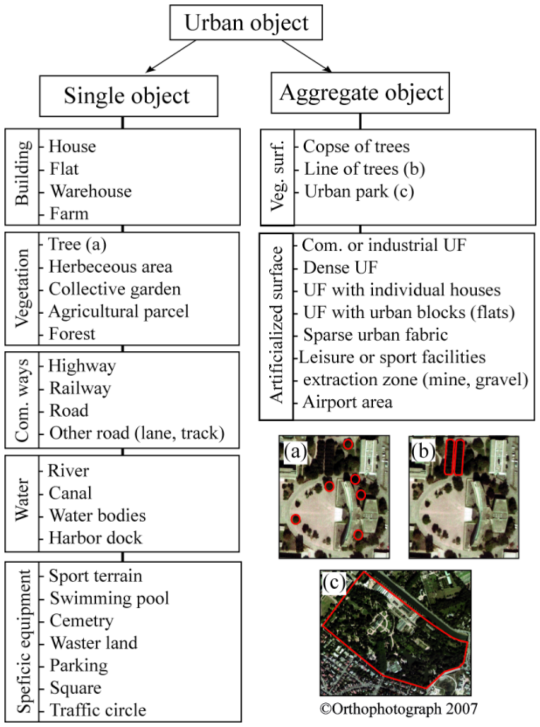

Figure 1: Dictionary of urban objects

Regarding the spatial relationship, five classical relations used in GIS have been selected (adjacency, inclusion, composition, alignment, distance).

Figure 2 shows a global view of the domain ontology. For sake of simplicity, we only show the hierarchy's higher concepts. In particular, relations between concepts, such as composition or inclusion (which correspond to OWL *Object_Properties*) are omitted in the figure.

Spatial_Relationship concepts correspond to:

- the set of RCC8 (Region Connection Calculus) spatial relationship, which have been reified to allow a consistent computation of the composition table (Marc-Zwecker et al., 2013).
- the distance relation, which is also reified to connect two objects with a value.

The *Geo_Object* property concept allows the definition of all the attributes which characterize a *Geo_Object* (size, shape, texture, resolution). The experts geographers usually associate these attributes to qualitative values, e.g. large, medium, or small for the size, rectangular or circular for the shape, homogeneous or heterogeneous for the texture.

2.2 The image ontology

Let us note that, as for the domain ontology, only the hierarchy's higher concepts are shown in the figure

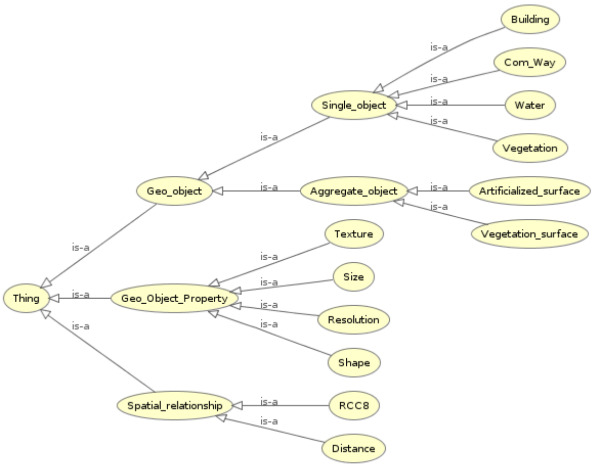

Figure 2: Domain ontology's higher level concepts

3. Transversal relations between concepts are also omitted for sake of simplicity. The higher level concepts of the image ontology have the following meaning: a satellite image (instance of *Image* concept), is composed by a set of disjoint segments (instances of *Image_Segment* concept). The aim of our image processing is to correctly assemblate the *Image_Segment* individuals in order to form an *Image_Object* individual. Actually, an ideal segmentation could allow the fusion of the concepts *Image_Segment* and *Image_Object*. Unfortunately, in practice, within a VHR urban image, the object of interest is generally associated to a set of segments (e.g. a roof is divided in (at least) two segments, corresponding respectively to the sunny and shadowy slopes).

The *Image* concept is described by the *Image_Property* concept, which characterizes the image itself:

- acquisition properties, such as the type of sensor used (e.g. LANDSAT, SPOT);
- location properties, such as georeferenced parameters, or the geographical region (e.g. Strasbourg, South of France, etc.).
- temporal properties, such as the date and the hour, the season, etc.
- spatial properties, such as resolution.

These meta-data are very important for selecting the rules that will be suitable. In particular, contextual knowledge can play an essential role, such as for instance the region (e.g. roofs in the South of France are mainly orange), or the season (the vegetation is green in spring and yellow in autumn).

The *Image_Segment* concept is subdivided in three classes : *Built_Segment*, *Natural_Segment* and *Hybrid_Segment*. A *Natural_Segment* belongs to a primary class (water, shadow, vegetal, bare soil). A segment which is not Natural is a *Built_Segment* (road or building). The *Hybrid_Segment* is a fuzzy concept used to characterize segments which could belong to different classes (e.g. a shadow and vegetal segment). The *Image_Segment* concept is characterized by OWL Data Properties, such as spectral and spatial values and indices.

The *Image_Object* concept is described par *Image_Object_Property* concepts, which are global properties (size, texture, etc.) characterizing a group of segments.

Figure 3: Image ontology's higher level concepts

3 INTEGRATION OF FUZZY RULES IN THE ONTOLOGY

3.1 Fuzzy concepts

In the area of urban image recognition, fuzzy logic mechanisms are used to cope with the imprecision of acquired data (Shackelford and Davis, 2003; Sui, 1992). On the other hand, fuzzy logic's formalism is adequate for the expression of qualitative concepts (e.g. small, medium, and large) and allows to take into account the vagueness that is inherent to human natural language's descriptions. Consequently it is well-suited for handling rules formulated by experts (Dubois and Prade, 2006). We briefly recall the main fuzzy logic principles that are used in our approach.

3.1.1 Fuzzy set theory elements

Fuzzy set theory was proposed by (Zadeh, 1965) and aims to address vagueness and imprecise knowledge, by relaxing the notion of membership to a set. Formally, if X is the reference set, a fuzzy subset A of X is defined by the membership function $f_A(x)$, which assigns to every $x \in X$, a value in the real interval [0,1]. As in the classical set theory case, 0 corresponds to non-membership, and 1 to full-membership.

Membership functions are represented by fuzzy intervals. The most popular ones have a trapezoidal, triangular, left or right form (Straccia, 2005). The trapezoidal function $trz(x;a,b,c,d)$ is defined as follows :

$$trz(x;a,b,c,d) = \begin{cases} 0 & if x \leq a \\ (x-a)/(b-a) & if x \in [a,b] \\ 1 & if x \in [b,c] \\ (d-x)/(d-c) & if x \in [c,d] \\ 0 & if x \geq d \end{cases}$$

3.1.2 Fuzzy rules

When we consider a fuzzy rule of the form: "if X is A then Y is B", we need to quantify the degree of influence between the premise "X is A" and the conclusion "Y is B".

The fuzzy implication operator can be defined as: $f_R(x,y) = \phi(f_A(x), f_B(y))$, and several generalizations of classical logic implication exist. We have adopted Mamdani's inference (Mamdani, 1977), which is widely used in decision systems : $f_R(x,y) = min(f_A(x), f_B(y))$.

3.2 Fuzzy rules implementation in the ontology

We use Semantic Web Rule Language (SWRL) under Protege OWL2 to implement ontology's fuzzy rules, with Pellet Reasoner. Indeed, (Bobillo and Straccia, 2010) proposed a fuzzy ontology plugin under Protégé, but fuzzy concepts are modelled as annotations, and hence fuzzy classification of concepts is not straightforward. We have adopted the approach of (Fudholi et al., 2009), where fuzzy intervals are directly implemented through SWRL rules, thus allowing us to control the fuzzy classification process within the ontology.

We show in figure 4 an example of the fuzzy trapezoidal intervals associated to shadow and vegetal segments, for spectral band 4 (Near Infra Red) values. In section 4 we will present the approach for learning such spectral values.

SWRL rules that calculate the membership function associated to the vegetal segment in figure 5 are directly deduced from the formulae of the trapezoidal function tr (x; 800, 1000, 1500, 1600) from figure

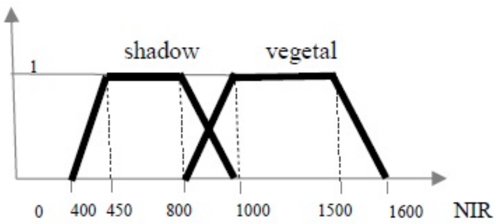

Figure 4: Fuzzy intervals associated to shadow and vegetal segments for NIR (Near Infra Red) values

4 (a=800, b=1000, c=1500, d=1600). The SWRL syntax is used, and `vegetal_band4(?s, ?x)` represents, for the analyzed segment ?s, the value ?x of its membership to a vegetal segment, with relation to the NIR (Near Infra Red) band value. Below 800 and above 1600, the inferred membership value is equal to zero (the corresponding rules are not shown).

```
Image-Segment(?s), band4(?s, ?b4),
  greaterThanOrEqual(?b4, 800.0f),
  lessThan(?b4, 1000.0f),
  subtract(?sub, ?b4, 800.0f),
  divide(?div, ?sub, 200.0f)
  -> vegetal_band4(?s, ?div)

Image-Segment(?s), band4(?s, ?b4),
  greaterThanOrEqual(?b4, 1000.0f),
  lessThanOrEqual(?b4, 1500.0f)
  -> vegetal_band4(?s, 1.0f)

Image-Segment(?s), band4(?s, ?b4),
  greaterThan(?b4, 1500.0f),
  lessThanOrEqual(?b4, 1600.0f),
  subtract(?sub, 1600.0f, ?b4),
  divide(?div, ?sub, 100.0f)
  -> vegetal_band4(?s, ?div)
```

3.3 Fuzzy classification strategies

The inference mechanism is based on Mamdani's inference (Mamdani, 1977), with two alternative strategies for the calculation of the membership value associated to the rule's premises:

- in the first strategy, the calculated membership value corresponds to the minimum of membership values of the premise's elementary fuzzy propositions. We call this strategy CMI, for Classical Mamdani Inference ;
- in the second strategy, the calculated membership value corresponds to the weighted average of membership values of the premise's elementary fuzzy propositions. We call this strategy WAMI, for Weighted Average Mamdani Inference.

In our approach, the conclusion function trivially corresponds to the searched membership degree (e.g. the degree for "is vegetal"). Therefore the conclusion can be merely modelled by the identity function with a membership degree of 1. Hence, the Mamdani's inference simply consists in copying the membership degree that has been computed for the rule's premise (by any of the strategies) into the conclusion's membership degree.

The defuzzification process will consist in applying the "Smallest of Maximum" method, thus returning the value of the membership degree calculated by the Mamdani's inference.

The final crisp decision (e.g. vegetal segment) is then submitted to a threshold (e.g. 0.7). Within our method, a segment can be classified into different classes (e.g. vegetal and shadow) with distinct membership values, since this corresponds to the reality (e.g. the shadow on a meadow).

The following SWRL rule illustrates the WAMI strategy, where we consider a simple average (i.e. the same weight for all the rule's premisses). The predicates `vegetal_band3`, `vegetal_band4`, and `vegetal_ndvi_index`, respectively give the values of blue band, NIR band, and Normalized Difference Vegetation Index for a given segment.

```
Image-Segment(?s),
  vegetal_band3(?s, ?vb3),
  vegetal_band4(?s, ?vb4),
  vegetal_ndvi_index(?s,?vnd),
  add(?add1,?vnd, ?vb4),
  add(?add,?add1,?vb3),
  divide(?div,?add,3)
  -> is_vegetal_segment(?s, ?div)
```

3.4 A multi-level methodology for urban object classification in the ontology

Our methodology of semi-automatic urban object recognition is under implementation. It based on the following steps:

- the satellite image to analyse is first segmented, using an image segmentation algorithm. The obtained segments with their attributes are then loaded in the image ontology under the Protégé-OWL2 editor. Every segment is entered as an individual in the *Image_Segment* class, and its attributes are associated to OWL Data Properties (see figure 5).
- all the individuals corresponding to image segments are then classified in the image ontology, with the type of fuzzy SWRL rules that we have presented in the previous section. This first classification is based on the segments' spectral properties, and gives the primary class (vegetation, water, shadow, etc.).
- the adjacent segments which belong to the same primary class after the spectral classification are then grouped, to constitute *Image_Object* individuals. At this stage, some spatial criteria can be used. For instance, the adjacency to segments of shadow allows the detection of buildings.
- finally, the obtained *Image_Object* individuals are compared to the domain ontology's *Geo_Object* concepts, in order to improve the classification. For example, object's attributes such as shape or size will allow to verify if an *Image_Object* individual classified as a house, corresponds to a house description according to the domain ontology.

As we have stated before, the result of the fuzzy classification can propose one or several *Geo_Object* classes for the same *Image_Object* individual, with distinct membership degrees. This methodology is currently under development, and so far, we have partially implemented all the steps except the last one.

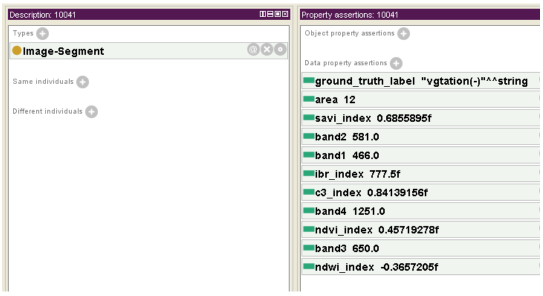

Figure 5: A segment's description under Protégé editor

4 Experimentation and evaluation results

4.1 Learning of the fuzzy rules

In these experiments, we used a Pleiades[1] image of the city of Strasbourg (France) acquired in 2012 and having a resolution of 0.7m/pixel and a size of 9211x11275 pixels. We extracted an area which presents all the interesting thematic classes we wanted to identify. Figure 6 presents the segmentation of the area that was used to learn the fuzzy rules (400x650 pixels).

[1] Pleiades: Dual optical system for metric resolution observations (CNES, France)

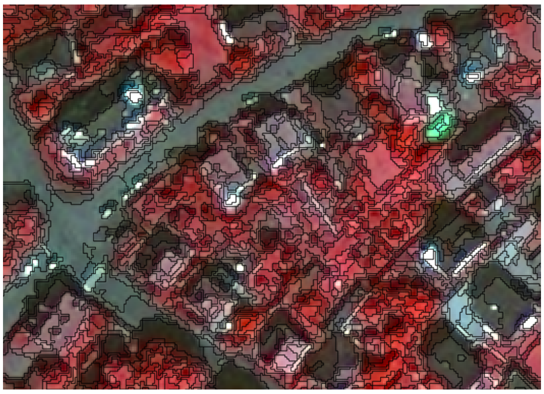

Figure 6: Segmentation used for the learning of the fuzzy rules

The spectral fuzzy rules were built based on the standard attributes and spectral indexes found in literature, such as NDVI (Normalized Difference Vegetation Index) or NDWI (Normalized Difference Water Index) (Sebari and He, 2013; Bouziani et al., 2010). To get better rules, more adapted to our type of images, we tried to combine experiments with theoretical values. We obtained the experimental values using a set of samples, extracted by geographical experts. The images were segmented using the Meanshift algorithm (Comaniciu and Meer, 2002). Then, all the segments were labeled using six ground truth classes: vegetal, shadow, water, building, road and soil. The hybrid and unknown class contains the overlapped and non-identified segments. Table 1 resumes the number of labeled segments for each class.

Table 1: Number of labeled segments for each ground truth class used.

Vegetal	567
Shadow	279
Water	144
Road	86
Soil	113
Building	253
Building (Wall)	44
Hybrid and unknown	477
Total	**1963**

4.2 Validation

To validate our approach, we have tested the fuzzy rules that we implemented in SWRL language under Protégé 4.3. We have carried out a two-stage validation. The first stage points out the effectiveness of the fuzzy rules in term of f-measure compared to crisp rules. Moreover, we compared the weighted average Mamdani inference (WAMI) to the classical Mamdani inference (CMI) for the considered example. In the second stage, the behavior of the fuzzy classification was visually analyzed in different types of areas, which were extracted of the same global image of Strasbourg region.

For the first scenario, the precision, recall and f-measure criteria have been calculated.

$$precision = \frac{t_p}{t_p + f_p} \tag{1}$$

$$recall = \frac{t_p}{t_p + f_n} \tag{2}$$

$$f-measure = \frac{2.precision.recall}{precision + recall} \tag{3}$$

where t_p stands for true positive (i.e. the number of items correctly labeled as belonging to the positive class), f_p for false positive (i.e. number of items incorrectly labeled as belonging to the class) and f_n for false negative (i.e. items which were not labeled as belonging to the positive class but should have been).

4.2.1 Comparison of crisp and fuzzy classification rules

In this first experimentation, we have used four types of rules:

- rules based on the small crisp interval (core)
- rules based on the large crisp interval (support).
- rules based on the fuzzy WAMI strategy with a threshold of 0.7,
- rules based on the fuzzy CMI strategy with a threshold of 0.7.

Table 2 shows that the precision obtained with small interval is obviously superior to the precision obtained with large and fuzzy intervals but with the lowest recall (and vice versa). The fuzzy interval obtained by applying the WAMI strategy gives the best f-measure which represents the best compromise between precision and recall. However, in the particular case of shadow class, the CMI strategy gives the best f-measure, while the WAMI strategy gives the best recall, which seems more interesting for the classification. Indeed, we observed that shadow segments belonging to other classes, e.g. vegetal, are detected as being simultaneously shadow and vegetal segments. Thus we assume that during the next step of the methodology, the use of spatial rules will enhance the precision. Moreover, as we have already pointed, getting the maximum recall for the shadow segments is useful for buildings detection. Consequently, in this experimentation, the WAMI strategy

Table 2: Results of the comparison among fuzzy rules (WAMI and CMI strategies with threshold=0.7) and crisp rules.

	Small interval			Large interval			Fuzzy interval WAMI			Fuzzy interva CMI		
	Pr	Rec	F-meas	Pr	Rec	F-meas	Pr	Rec	F-meas	Pr	Rec	F-meas
Vegetal	0.988	0.155	0.267	0.763	0.966	0.852	0.876	0.864	**0.87**	0.963	0.47	0.63
Shadow	0.864	0.433	0.576	0.257	1.0	0.408	0.572	**0.967**	0.718	0.92	0.63	**0.74**
Water	0.99	0.71	0.82	0.73	0.965	0.831	0.969	0.881	**0.922**	0.984	0.861	0.917
Soil	0.368	0.371	0.369	0.148	0.991	0.257	0.376	0.672	**0.482**	0,42	0.292	0.344

is the best suited to the classification of image segments.

4.2.2 Visual evaluation

To confirm the quality of the results, we also proposed a visual evaluation. Figure 7 presents the result of the detection obtained applying the fuzzy rules with the WAMI strategy to an urban area, similar to the one used for learning (375x399 pixels). We have superposed over the original image the result of our classification : green areas have been classified as vegetation, yellow areas have been classified as shadow, and red areas correspond to unclassified areas (mostly vegetation or shadow).

Figure 7: Classified urban area

5 CONCLUSIONS

We have presented an original work, that attempts to show the effectiveness of ontologies' use in the domain of urban object recognition from VHR satellite images. The proposed methodology is under development and aims to address the semantic gap and symbol anchoring problems, by providing explicit correspondence mechanisms between an abstract ontology, which qualitatively describes the domain's concepts, and a concrete ontology, which quantitatively describes the image objects.

Our work takes into account the uncertainty that is inherent to the acquired data by the implementation of fuzzy rules in the ontology.

So far, our methodology's implementation allows the fuzzy classification of image segments into primary classes (vegetal, shadow, water, bare soil, building). When the spectral classification does not affect a segment to a primary class, the system deduces that it belongs to an artificial class (building or road). The distinction between building and road will be done in a later stage, by using the adjacency to shadow (a building is adjacent to a shadow, a road is not).

The grouping of segments of the same primary class into image objects and the buildings detection are being currently developed. The step of matching between the domain ontology and the image ontology will be first applied to the buildings construction. Indeed, at the current stage, the adjacency to shadow allows the detection of some segments belonging to the buildings. But unlike the case of objects belonging to primary classes (vegetation, water, etc.), the assembly of segments belonging to a building is very difficult because roofs are dissimilar and their spectral properties are not stable. It will then be essential to find the general characteristics of the houses (shape, size, etc.) in the domain ontology to help the grouping of buildings' segments.

A medium term perspective of our work is to integrate the fuzziness in all stages of the methodology, and particularly in the image segmentation process.

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