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Coastal image interpretation using background knowledge and semantics

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Abstract

In this article, we present a framework to model and to use knowledge provided by experts for remote sensing image interpretation of coastal area. The goal of this approach is to associate semantic to regions issued from the segmentation of an image. The idea is to start with a raw description of the knowledge given by the expert on the different thematic object classes present in the image. This knowledge is then decomposed and formalized to be usable during the classification process. A first interpretation of the image is computed through an ontology with spectral information about the classes. Then, a set of Knowledge Functions (KFs) are defined according to the description of the expert's knowledge. These KFs are then used to check the consistency of the spectral interpretation and to detect potentially mislabeled regions. The interpretation of these regions is revised in an iterative process to produce a more accurate final result. Experiments on remote sensing images of a coastal zone of Normandy, France are presented to show the relevance of the method.

Keywords: knowledge-based image interpretation, ontology, coastal management

1. Introduction

Image interpretation consists in extracting the meaning from data issued from a scene. It means structure the data, identify the different objects composing the image, understand their spatial organization and build a description of the scene. Consequently, the image interpretation task needs and uses a lot of *a priori* knowledge:

- on the scene and on the objects ;
- on the relations between these objects ;
- on the domain of application.

This *a priori* knowledge is often known by the expert who wants to interpret the image but the challenge is to find a way to *transfer* it to the machine. This problem is also known as the *semantic gap* which can be defined as the difficulty to link the information extracted from the data (often as numerical values) and knowledge provided by the experts (often provided as free-speech description). With the development of Very High Spatial Resolution (VHSR) imagery, fully manual interpretations are not possible any more. In order to help the experts in interpreting the images, efficient tools have to be developed. To achieve good results, these tools need to use all the knowledge available for the interpretation task.

This need for knowledge formalization led the researchers to propose new approaches which can leverage from the information provided by the experts. These *knowledge-based* approaches are more and more ubiquitous and represent the future of image interpretation [1, 2, 3]. The challenge is to represent the knowledge at different levels (*e.g.* objects, scene, domain, etc.) and to translate it into semantics. The advent of the object-oriented paradigm, which consists in the segmentation of the image before the interpretation, speeded up the development of the knowledge-based approaches. Indeed, this paradigm provides a new frame of reasoning as the expert can directly provide the knowledge he experiences in the real life on the geographical objects.

In this article, we present a framework to represent the knowledge of the expert about objects in an image. It is based on the knowledge representation presented in [4] which models the object classes to find in the image as a hierarchy of classes. The contribution of this paper is twofold. First, we extend this representation by decomposing the expert knowledge into several Knowledge Functions (KFs). Second, we improve this representation with new type of expert knowledge: spatial relations between objects. Indeed, different kinds of knowledge have been acquired from coastal remote sensing image interpretation experts. From this knowledge, we proposed a representation using KFs to model the different acquired knowledge. While these KFs are relatively simple, experiments

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on coastal image interpretation revealed their usefulness to accurately represent the expert knowledge. This modular approach allows the method to use very heterogeneous knowledge (*e.g.* spectral, spatial, contextual, etc.) in an unifying way.

The article is organized as follows. First, an overview of related knowledge-based image interpretation methods is introduced in Section 2. Our approach of knowledge representation is then presented in Section 3. Section 4 shows an experimental evaluation of the developed method on coastal remote sensing image. Finally, conclusions are drawn in Section 5.

2. Related work

With the first object-oriented analysis methods appearing in the 1990's, techniques such as the use of knowledge based systems and artificial neural networks came up to offer much potential for the extraction of geographical information from remote sensing imagery. For example, [5] proposed an integrated approach leveraging from both GIS information and remote sensing. Thematic object data are used to improve the classification accuracy by defining specific *a priori* probabilities for each object. The same kind of idea is developed in [6], where the authors exposed a methodology of data integration of remotely-sensed raster data with vector data. In [7], the authors present how object classification and aggregation hierarchies can be used to describe relationships between terrain objects. They also show that the categorization of the different types of object can be partly based on these hierarchies.

In more recent years, different propositions were introduced to leverage from expert knowledge in remote sensing image classification. We can cite [8] who proposed to integrate image processing, digital elevation data and field knowledge or [9] who developed a system called geoAIDA, which uses semantic network to model *a priori* knowledge about the scene, sensors and operators. Using structural knowledge was also considered to improve the classification of remote sensing image. In [10], a first pixel-based classification is computed. Then, the class affected to the pixel can be altered according to information about the shape of and the spatial relations between the regions that are to be determined. [11] proposed a specialized approach using a context-sensitive Bayesian network for semantic inference of segmented scenes. The regions' remote sensing related semantic classes are inferred in a multistage process based on their spectral and textural characteristics as well as the semantics of adjacent regions. Another system presented by [12] is composed of a content-based multimodal Geospatial Information Retrieval and Indexing System (GeoIRIS) which includes automatic feature extraction, visual content mining from large-scale image databases, and high-dimensional database indexing for fast retrieval. Facing the difficulty of the of modeling of expert knowledge, [13] presented a clear list of the specific challenges of the geoscience and geography fields for knowledge representation.

In order to improve image interpretation, several different systems, approaches and platforms have been proposed. [14] developed a GIS-based neuro-fuzzy procedure to integrate knowledge and data in landslide susceptibility mapping. It employs a fuzzy inference system (FIS) to model expert knowledge, and an artificial neural network (ANN) to identify non-linear behavior and generalize historical data to the entire region. The results of the FIS are averaged with the intensity values of existing landslides, and then used as outputs to train the ANN. Alternatively, [2] proposed a system for the annotation of large satellite images using semantic classes defined by the user. This annotation task combines a step of supervised classification and the integration of the spatial information. Given a training set of images for each class, learning is based on the latent Dirichlet allocation (LDA) model.

The use of ontologies to represent the semantics of geoscience domain knowledge was introduced by [15] who proposed a GIS architecture that enables geographic information integration in a flexible way based on its semantic value and regardless of its representation. More recently, [16] developed a collection of ontologies using the web ontology language (OWL) that include both orthogonal classes (space, time, Earth realms, physical quantities, etc.) and integrative science knowledge classes (phenomena, events, etc.). Their article describes how to build a knowledge base for geosciences and related classes using ontologies. In [17], the authors analyze and compare the most widely referred proposals of geographic information integration, focusing on those using ontologies as semantic tools to represent the sources, and to facilitate the integration process. [18] describe an information model for a geospatial knowledge infrastructure that uses ontologies to represent these semantic details, including knowledge about domain classes, the scientific elements of the resource (analysis methods, theories and scientific processes) and web services. This semantic information can be used to enable more intelligent search over scientific resources, and to support new ways to infer and visualize scientific knowledge.

In this paper, we propose a recognition method based on an ontology, which has been developed by experts of the domain. In order to give a semantic meaning to the objects, we use the matching process between an object and the classes of the ontology developed in [4]. This method is extended and generalized by introducing a new kind of knowledge about the spatial relationships between geographical objects. Moreover, we choose another domain of application (coastal area analysis), to show that, in contrast to several related work, our method is generic and can easily be extended by defining new types of knowledge functions.

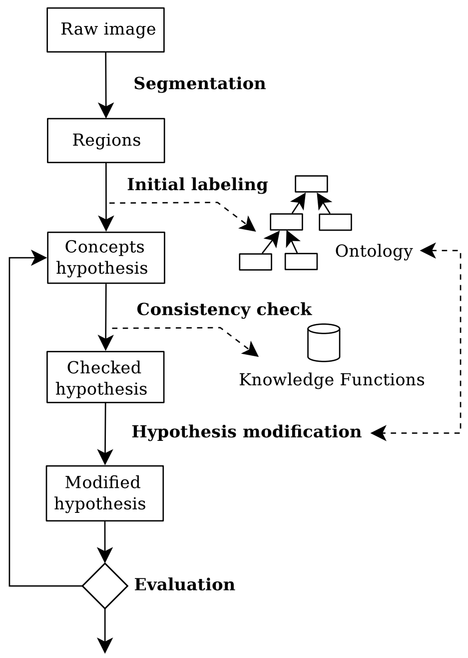


Figure 1: Flowchart describing the different steps of the approach.

3. Description of the method

In this section, we describe the method we developed for image interpretation using knowledge and semantics. In Fig. 1, we present the different steps of the approach. The first step is the segmentation of the image in order to produce a set of regions. In a second step, an initial labeling of the regions is carried out using an ontology composed of a hierarchy of classes. This ontology contains for each class, a set of information about the spectral properties of the classes and allows us to make some hypothesis about the semantic of the regions. In a third step, additional knowledge provided by the expert are translated in KFs. They are then used for a consistency checking on the hypothesis provided by the ontology containing the spectral information. The hypothesis are therefore modified to improve the consistency of the scene (*i.e.* the labeling of the regions and the KFs). This process iterates while the consistency of the scene increases.

If $\mathfrak{R}$ is the set regions issued from the segmentation of an input image, the aim of the method is to find the best class for each region r ($\in \mathfrak{R}$) according to the spectral information stored in the ontology and the knowledge defined in the KFs. We assume that $\mathfrak{R}$ is a partition of the image, so that there no holes or overlaps between the regions. Another strategy could consist in creating the regions by using the knowledge as proposed in [19] or [20].

3.1. Initial labeling

To be able to use the knowledge defined by the expert about the classes, we have to compute an initial labeling of the regions of $\mathfrak{R}$. Indeed, the knowledge we want to describe can only be manipulated if an initial semantic is present. For example if you want to check if it is consistent to have a *building* region surrounded by *water* regions you need a first proposition of the *semantic* (*building, water,* etc.) of the different regions.

In order to produce this initial labeling we defined an ontology of coastal objects (see Fig. 2). This ontology is a hierarchy of classes, which can be seen as classes of objects, corresponding to the geographical objects the expert wants to detect in the images. Each class is described by a set of attributes corresponding to the range of accepted values for a given spectral band. This knowledge have been acquired thanks to the experience of the geographer expert on the spectral reflectance of the different object, by manual observation and using machine learning tools [21]. These ranges of values are not as accurate as a supervised classifier but the idea is not to have a *perfect* labeling but a *first* labeling. This first labeling will then be improved through a refinement step using the other knowledge of the expert about the different objects.

To calculate this first labeling we used the procedure exposed in [4]. The method is based on a matching score defined as a linear combination of local similarity measures. First, the complete path starting from the root of the ontology and ending at the studied class is computed. Then, for each class of the path, the local similarity measure is calculated, by comparing the features of a region with the specific attributes of the class. Finally, an algorithm is proposed to traverse the ontology to find the best class(es) according to the matching score for a region. After the step of ontology based object recognition, each region r of $\mathfrak{R}$ has a set of hypothesis with a score value (s_i) associated to each hypothetical class (c_i).

Let $\mathcal{C}$ be the set of classes present in the ontology (*i.e.* corresponding to the leaf classes of the hierarchy). It is possible to define the set of hypothetical classes for a region r as:

$$\mathcal{H}^{(r)} = \{(c_i, s_i) | \quad c_i \in \mathcal{C}, s_i \in [0;1], 1 \leq i \leq card(\mathcal{C}), s_i \geq s_{i+1}\} \tag{1}$$

where c_i is the label of the class and s_i the score of the region for this class. The exact definition and calculation procedure of s_i is presented in details in [4].

The best hypothesis class for a region r is then defined as:

$$\mathcal{B}(r) = (c, s) \mid \nexists\ s_i > s\ \forall (c_i, s_i) \in \mathcal{H}^{(r)} \tag{2}$$

It means that $\mathcal{C}$ forms a thematic partition of the set of all identified objects, *i.e.* each object is assigned to exactly one class of $\mathcal{C}$: the best hypothesis $\mathcal{B}(r)$. The example below presents a possible list of hypothesis for a region.

Example 1 Example of a set of hypothesis for a region r: $\mathcal{H}^{(r)} = \{$(Field, 0.716), (Wooded area, 0.670), (Salt meadow, 0.533), (Dune, 0.427), (Pond, 0.307), (Building, 0.087), (Slikke, 0.020), (Beach, 0.001)$\}$ and $\mathcal{B}(r) =$ (Field, 0.716). These values were computed by comparing the features of the region and the characteristics of the classes [4].

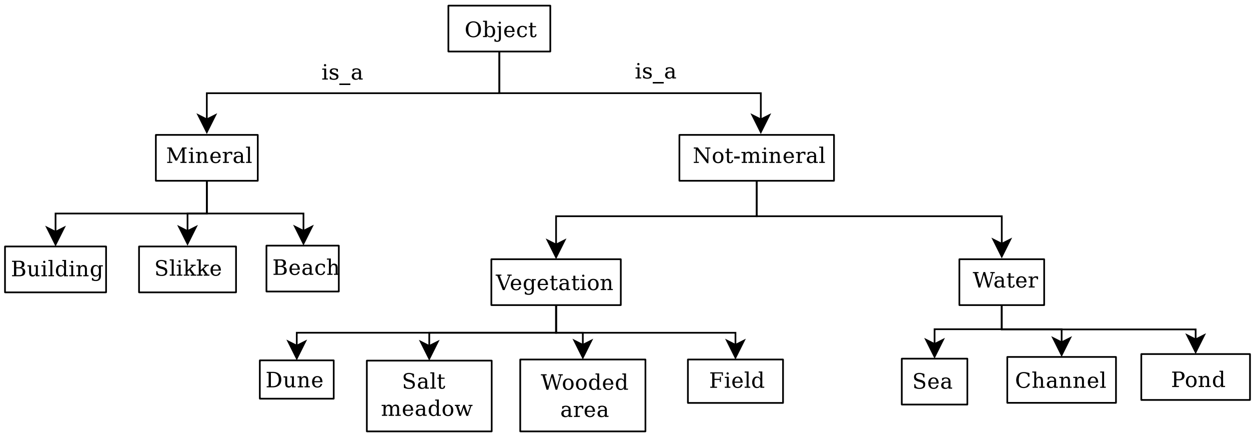


Figure 2: The ontology presenting the different coastal objects.

3.2. Additional knowledge acquisition

Along with the definition of the ontology using only the spectral information, the expert has also produced a set of raw knowledge that he knows about different coastal objects. The Tab. 1 presents the different observations for each class. From these different information an extended model of the ontology has been defined (see Fig. 3). This knowledge has been acquired by interview amongst geographer experts and illustrates the consensual observation made on the different classes.

3.3. Representation of the knowledge

Each KF takes a region r as input and evaluates the concordance between the knowledge described by this KF and the properties of the region. A fuzzy value v $(\in [0;1])$ is computed to quantify the concordance between the region and the knowledge defined in the function. Consequently, all the KFs have the same prototype ($KF : r \rightarrow v$ $(\in [0;1])$) to be easily used and combined. Furthermore, each KF comes with a weight w $(\in [0;1])$ which is set according to the importance and the confidence of the expert on the knowledge represented by this KF (the default value is set to 1). The weights can be difficult to select and are specific to a certain type of application. For example, according to the context of the scene (*e.g.* urban area, coastal area, etc.), certain types of knowledge are more useful to identify specific object classes. For example, it is difficult to use knowledge on the elevation in urban area due to many artifacts (*e.g.* bridge, cars, etc.). On the contrary, this knowledge is interesting in coastal area where the landscape is generally simple. The weights are generally adjusted by the expert using a trial-error approach, or by using optimization approach [19].

The set $\mathcal{F}$ is composed of different KFs built to represent the knowledge of the expert. Each of these KFs represents one part of the knowledge of the expert. This decomposition in KFs allows the user to define different kinds of knowledge about the classes. Furthermore, some classes could have more detailed knowledge and consequently more or less KFs defined on them.

In the following, we detail the definition of different KFs which have been created according to the knowledge expressed by domain experts on coastal objects (see Tab. 1). The set of functions $\mathcal{F} = \{\mathcal{O}, \mathcal{S}, \mathcal{E}, \mathcal{N}, \mathcal{D}\}$ describes the different kinds of knowledge that we have extracted from the raw knowledge:

- $\mathcal{O}(r)$ returns the score associated to the best ontology hypothesis.
- $\mathcal{S}(r)$ evaluates the correspondence between the knowledge on the shape of a class and a region.
- $\mathcal{E}(r)$ evaluates the correspondence between the knowledge on the elevation of a class and a region.
- $\mathcal{N}(r)$ evaluates the correspondence with the knowledge of the potential classes in the neighborhood of a region.
- $\mathcal{D}(r)$ evaluates the correspondence between the knowledge about distance to other classes of a region.

3.3.1. Definition of the function $\mathcal{O}$

The function $\mathcal{O}(r)$ returns the score of the best ontology hypothesis amongst $\mathcal{H}^{(r)}$. It is defined as:

$$\mathcal{O}(r) = s \mid (c, s) = \mathcal{B}(r) \tag{3}$$

Example 2 Using the Example 1, the best ontology hypothesis function returns: $\mathcal{O}(r) = 0.716$ as $\mathcal{B}(r) =$(vegetation, 0.716).

3.3.2. Definition of the function $\mathcal{S}$

The function $\mathcal{S}(r)$ is used to check if the region has the expected shape according to the best ontology hypothesis for this region. For example, for the region where the best hypothesis is *building*, we have to check that the shape is *compact* (see Table 1). The notion of shape is very difficult to represent and a discussion has been carried out with

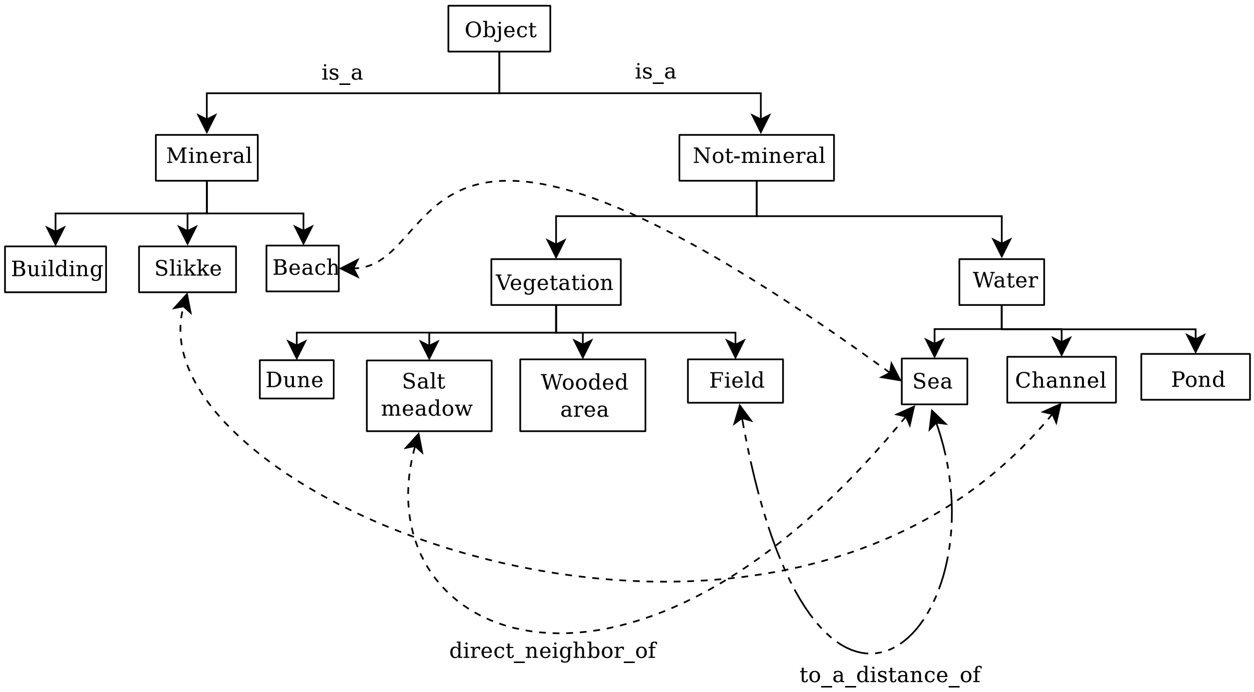
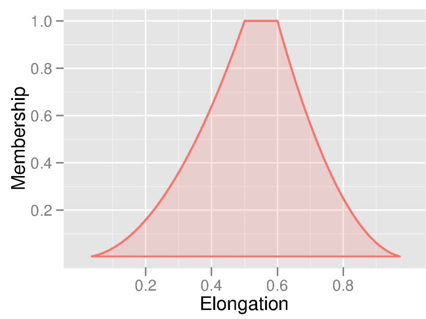
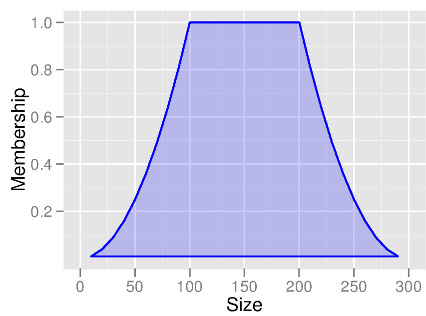


Figure 3: The ontology of coastal objects extended with expert knowledge (only a part of the knowledge is represented for visual convenience). Dotted arrows represent the two new types of relations between the classes: *to a distance of* and *direct neighbor of*.

the expert to formalize their knowledge into a computer usable form. For each shape information, a shape index has been selected. For each shape index an interval of accepted values for this index has been chosen according to the knowledge of the shape of the class. Tab. 2 summarizes the different shape indexes and related accepted values for these indexes. To check if a class hypothesis is consistent with the shape information, we computed a fuzzy value using a simple membership function. The Fig.4 presents an example of the functions defined using the range of accepted values of the elongation (a) and size (b).



(a) Membership function for the elongation.



(b) Membership function for the size.

Figure 4: Example of two functions used to compare the shape of a region and the knowledge of the expert.

3.3.3. Definition of the function $\mathcal{E}$

The function $\mathcal{E}(r)$ checks if the elevation of the region is correct according to the best hypothesis class of the region. The knowledge in Tab. 1 gives two different kinds of information: a knowledge about the average elevation for the class and a knowledge about the lack of variation in the elevation of the region. Consequently, two functions were defined to check these constraints.

To check if the region matches with the elevation constraint for a class, we computed the mean $\mu_e^{(r)}$ and standard deviation $\sigma_e^{(r)}$ of the elevation of the region. In order to verify if the elevation matches with the knowledge of expected average elevation, we compared the mean elevation to the threshold defined by the expert:

$$\mathcal{E}(r) = \begin{cases} 1 & \text{if } \mu_e^{(r)} \ (\leq \text{ or } \geq) \ elevation_{threshold} \\ 0 & \text{else} \end{cases} \tag{4}$$

Table 1: Raw knowledge about the different coastal classes of object.

	Classes	*Knowledge*
Mineral	Building	Neighbors: Wooded area, Pond Compact form
	Slikke	Neighbors: Salt meadow, Channel, Sea, Beach
	Beach	Neighbors: Slikke, Sea Linear form
Vegetation	Dune	Neighbors: Beach Elevation $> 5m$ Altitude variation $(\pm 5m)$
	Salt meadow	Neighbors: Slikke Distance to the sea: $[5;6]m$ Distance to a channel: $[5;6]m$ Elevation $< 5m$ No altitude variation
	Wooded area	Neighbors: Building, Field Surface: $[100;200]m^2$
	Field	Distance to the sea: $[15;20]m$ Rectangular form
Water	Pond	Neighbors: Salt meadow, Wooded area, Building Surface: $[100;200]m^2$
	Sea	Neighbors: Slikke, Beach, Channel, Salt meadow
	Channel	Neighbors: Slikke Linear form

Table 2: Shape index selected to represent expert knowledge.

Concept	*Shape*	*Shape index*
Building	compact shape	elongation $\in [0.5, 0.6]$
Beach	linear shape	elongation $\in [0.8, 0.9]$
Field	rectangular form	Miller index $\in [0.7, 0.9]$
Pond	size constraint	size $\in [100, 200]$
Wooded area	size constraint	size $\in [100, 200]$

A second function is defined to check the constraint of the lack of variation in the elevation of the region:

$$\mathcal{E}(r) = \begin{cases} 1 & \text{if } \sigma_e^{(r)} \leq elevation_{threshold} \\ 0 & \text{else} \end{cases} \qquad (5)$$

3.3.4. Definition of the function $\mathcal{N}$

The neighbors information is more and more interesting in object oriented image analysis. As we deal with objects, a strong knowledge about neighboring objects if often available but rarely used. The aim of this function is to compute a value according to the neighbors of each region to check and quantify if the region is immersed in a possible context according to expert knowledge. For example, if we find a *building* region surrounded by *water* regions, we might have detected an error. This function is defined to represent this knowledge and to takes advantage of it.

According to the best hypothesis of the regions of the set of regions surrounding the region r ($\mathfrak{N}(r)$) (*i.e.* regions

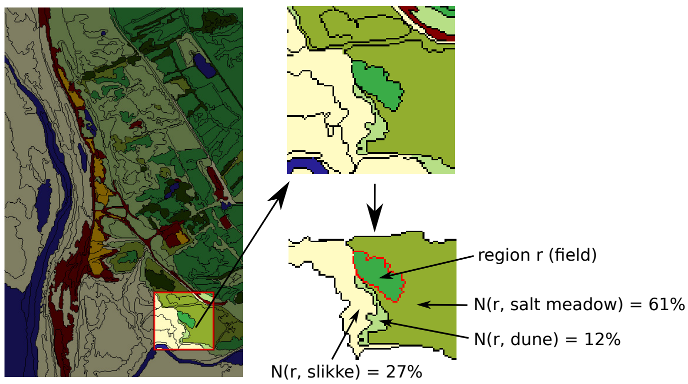


Figure 5: Example of computation of the neighborhood of a region. The regions directly adjacent to the region r are considered as in its neighborhood. The percentages are defined as the ratio of the number of the pixel of each region over the sum of the number of pixels of all the regions in the neighborhood of r. This information is used to evaluate if the neighborhood of a region is coherent.

topologically adjacent to the region r), a value quantifying the presence of a class in the neighborhood of the studied region is computed as:

$$\mathbb{N}(r,c) = \frac{1}{\sum\limits_{r_i \in \mathfrak{N}(r)} card(r_i)} \cdot \sum_{\substack{r_i \in \mathfrak{N}(r) \\ c = c_i \\ (c_i, s_i) = \mathcal{B}(r_i)}} card(r_i) \qquad (6)$$

with $card(r)$ the cardinality (*i.e.* the number of pixels) of the region r.

The function $\mathbb{N}$ is computed for each class surrounding the region r. The Tab. 3 illustrates the possible neighboring classes which have been derived from Tab. 1. In this table, the + symbol means that the two classes can be neighbors, while a − symbol means the contrary. Using this information, we computed a value which quantifies if the neighboring regions of a a given region are in concordance with the expert knowledge:

$$\mathcal{N}(r) = \frac{\sum_{r_i \in \mathfrak{N}(r)} \mathbb{N}(r_i) \cdot neighbor(r, r_i)}{\sum_{r_i \in \mathfrak{N}(r)} neighbor(r, r_i)} \quad (7)$$

with *neighbor* a function which return 1 or 0 respectively for + or − according to the table 3.

Example 3: In Fig. 5, $\mathcal{N}(r)$ would be equals to zero as the regions belonging to the neighborhood of r (*Field*) are: *Slikke*, *Salt meadow* and *Dune* and according to Tab. 5, the regions of these object classes should not be in the neighborhood of a field. Consequently, the object class affected to this region has an important chance to be revised.

3.3.5. Definition of the function $\mathcal{D}$

The function $\mathcal{D}(r)$ is a function checking the consistency of the region according to the distance to an another object class. It starts from the region r and iteratively checks the class affected to the neighbors of r (*i.e.* $\mathfrak{N}(r)$). If a region t, belonging to the requested object class, is found by checking a predefined number of iterations of the neighbors, the distance between r and t is evaluated. This distance is computed as a pixel path between the centers of the bounding boxes of the two regions. This distance in pixel is then converted in meter using the spatial resolution of the image. This distance in meter is then compared to the knowledge in the Tab. 1 as a fuzzy matching similar to the one used for shape evaluation (see Fig. 4).

3.4. Evaluation of the result according to the knowledge

Now that we have defined a set of KFs we can use them to improve the quality of the initial labeling. It is important to remember that the aim of the first step is to generate a set of hypothesis for each region according to spectral information within the ontology. Then, for each region, we use the KFs defined for the best hypothesis of each region to evaluate the consistency of this hypothesis according to the context of the region. Indeed, each KF is not interesting for all the classes of the ontology. The Tab. 4 summarizes the different KFs defined according to the classes of the ontology.

To efficiently used the knowledge, we have to check for each region, if the hypothesis proposed by the ontology is consistent with the KFs defined by the experts. For this, a local function of knowledge agreement ($\mathbb{L}(r)$) is defined, computing the concordance between a region r and the subset of KFs ($\mathcal{F}^{(r)} \subseteq \mathcal{F}$) which are available for the best hypothetical class of the region r:

$$\mathbb{L}(r) = \frac{1}{\sum\limits_{f \in \mathcal{F}^{(r)}} w(f)} \cdot \sum_{f \in \mathcal{F}^{(r)}} (f(r) \cdot w(f)) \quad (8)$$

Then, the global function of knowledge agreement ($\mathbb{G}(r)$) is defined computing the function $\mathbb{L}(r)$ on all the regions of a segmentation:

$$\mathbb{G}(\mathfrak{R}) = \frac{1}{card(\mathfrak{R})} \cdot \sum_{r \in \mathfrak{R}} \mathbb{L}(r) \quad (9)$$

3.5. Modification of the result according to the knowledge

Now that we are able to evaluate the agreement of a region with the available knowledge we can use this information to detect potential errors in the interpretation. We defined an iterative algorithm whose steps are described in the following pseudo code:

Algorithm 1 Algorithm for evaluation of consistency of the scene

1: compute $\mathbb{G}(\mathfrak{R})$
2: find the region r_{min} with the $min(\mathbb{L}(r))$ among $\mathfrak{R}$
3: switch the class affected to the region r_{min} to the next hypothesis according to the set of hypothesis of this region
4: evaluate the relevance of this modification by recomputing $\mathbb{G}(\mathfrak{R})$
5: if $\mathbb{G}(\mathfrak{R})$ increases go to 2
6: else go to 2 and ignore current r_{min} in the next selection step
6: if all regions have been considered without improvement, exit.

The goal is to find at each step the region which minimize $\mathbb{L}(r)$. This region is consequently the region having the lower agreement with expert knowledge according to the class of the ontology affected to this region. Thus, in this step, we use the formalized knowledge to detect potentially mislabeled regions. Once the region minimizing $\mathbb{L}(r)$ identified, the class affected to the region is switched to the next potential class according to the set of hypothesis given by the ontology (see Eq. 1). The process iterates until $\mathbb{G}(\mathfrak{R})$ does not increase anymore, which ensures its termination. It might be interesting to check individually for each region if the concordance with the knowledge functions increases. However, the switch from one class to another affects also other regions of the result. For example, if we change the class of a region, the computation of the knowledge function of the regions surrounding this region can be modified. Consequently, even if checking locally the evolution of $\mathbb{L}(r)$ is interesting, a global evaluation of $\mathbb{G}(\mathfrak{R})$ is needed to assess globally the results according to local modifications. As this algorithm consists in simple iterations, it does not guarantee the convergence

Table 3: Knowledge about the neighborhood of the class of objects derived from expert knowledge of Tab. 1.

	Building	*Slikke*	*Beach*	*Dune*	*Salt m.*	*Wood.*	*Field*	*Pond*	*Sea*	*Channel*
Building		-	-	-	-	+	-	+	-	-
Slikke	-		+	-	+	-	-	-	+	+
Beach	-	+		+	-	-	-	-	+	-
Dune	-	-	+		-	-	-	-	-	-
Salt m.	-	+	-	-		-	-	+	+	-
Wood.	+	-	-	-	-		+	+	-	-
Field	-	-	-	-	-	+		-	-	-
Pond	+	-	-	-	-	+	-		-	-
Sea	-	+	+	-	+	-	-	-		+
Channel	-	+	-	-	-	-	-	-	+	

Table 4: KFs defined according to the different classes.

Class	*KFs*
Building	$\{\mathcal{O}, \mathcal{N}, \mathcal{S}\}$
Slikke	$\{\mathcal{O}, \mathcal{N}\}$
Beach	$\{\mathcal{O}, \mathcal{N}, \mathcal{S}\}$
Dune	$\{\mathcal{O}, \mathcal{N}, \mathcal{E}\}$
Salt meadow	$\{\mathcal{O}, \mathcal{N}, \mathcal{E}, \mathcal{D}\}$
Wooded area	$\{\mathcal{O}, \mathcal{N}, \mathcal{S}\}$
Field	$\{\mathcal{O}, \mathcal{D}, \mathcal{S}\}$
Pond	$\{\mathcal{O}, \mathcal{N}, \mathcal{S}\}$
Sea	$\{\mathcal{O}, \mathcal{N}\}$
Channel	$\{\mathcal{O}, \mathcal{N}, \mathcal{S}\}$

to a globally optimal but only to a local optimal (*i.e.* it is a greedy algorithm). This could be improved by using an optimization algorithm, as a genetic algorithm. Note that the algorithm is deterministic and provides always the same results according to an initial labeling using the ontology. Consequently, this approach is stable and experiments can be re-run without effort.

4. Experiments

In this section, we present experiments to illustrate the framework presented in the previous sections. Coastal landscapes are severely affected by environmental and social pressures. Their long term development is controlled by both physical and anthropogenic factors, which spatial dynamics and interactions may be analyzed by Earth Observation data. The Mont-Saint-Michel Bay (Normandy, France) is the European coastal system experiencing the highest tidal range (approximately 15m) because of its geological, geomorphological and hydrodynamical contexts at the estuary of the Couesnon, Sée and Sélune rivers. It is also an important touristic place with the location of the Mont-Saint-Michel Abbey, and an invaluable ecosystem of wetlands forming a transition between the sea and the land. These reasons make of this place an important area of study where the use of very high resolution imagery can play an important role. In these experiments, we used a Quickbird image acquired in 2006 having a resolution of 0.7m/pixel. We extracted an area which presents all the interesting thematic classes we wanted to identify. Fig. 6 (a) presents an extract the area (400x650 pixels).

We used the eCognition[1] software to obtain a segmentation of this image. Note that even if the method is to some extend dependent of the quality of the segmentation, another segmentation could have been used. The segmentation used in this experiment is presented on the figure 6 (b). We also possess for this area a LIDAR information which has been used to evaluate the elevation knowledge provided by the expert. An elevation map is presented on figure 6 (c) (the brighter, the higher). A groundtruth map have been provided by geographer expert for this area and is presented on Fig. 6 (d). This map presents the eight most important thematic classes present in this image: *Slikke*, *Beach*, *Dune*, *Field*, *Vegetation*, *Water*, *Building*, *Salt meadow*. Note that the Water class is the association of the classes Sea, Channel and Pond because the expert has not made any difference on these classes in this image.

After the segmentation step, we used our ontology storing the spectral information to obtain a first labeling of the area. Fig. 6 (e) presents the result of this first labeling. One can see that the results are interesting but a lot of small mislabeled regions are visually identifiable (for example the red building area in the middle of the slikke). We used this first labeling as the input of our iterative coherency checking approach. We used the KFs defined previously in the paper to evaluate the coherency of this labeling. The results at the end of the iterations is presented on the figure 6 (f). In this experiment, 84 iterations have been carried out. In order to evaluate the quality of this interpretation, we used the groundtruth provided by the expert to compute confusion matrices and the Kappa coefficient. Tab. 5 and Tab. 6 presents respectively the confusion matrix of the result before and after the application of the KFs. The Kappa value before the application of the KFs was equal to 0.776. The application the KFs allowed us to increase this value to 0.887. This good result highlights the benefit of using the knowledge of the expert

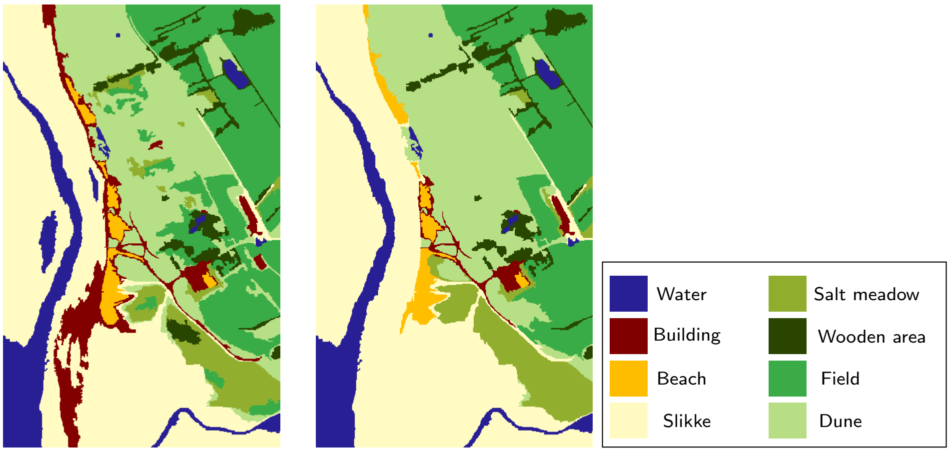
[1] http://www.ecognition.com/

(a) The raw image.

(b) The segmentation of the image (border of the region are highlighted in blank).

(c) The elevation map (the brighter, the higher)

(d) The groundtruth provided by the expert.



(e) The result before the application of the KFs.

(f) The result after the application of the KFs.

Figure 6: Images presenting several informations about the image used in the experiments on the Mont-Saint-Michel Bay, France captured with Quickbird (0.7m/pixel).

to improve image interpretation. Most of the remaining errors are due to the quality of the segmentation which stays a really decisive point in the interpretation process.

Of course, there is no interest of formalizing and using expert knowledge if the initial classification and labeling provide very accurate results. If the expert is able to bring many samples on each class, supervised classification could give relevant results. However, the aim of this paper is to show how expert knowledge can be modeled and used to increase the accuracy of a classification calculated without enough samples and of insufficient quality. Moreover, as we propose to use a simple initial classification based on intervals of values and not on samples from the image, this classifier can be used on many different images, without having to provide new samples from each image.

5. Conclusion

In this paper, we have presented a framework for knowledge-based image interpretation of coastal images. This approach uses an ontology of coastal objects to affect a semantic to the regions extracted from a segmentation. This semantic is then refined using Knowledge Functions (KFs). These KFs have been designed to translate the knowledge of the expert about coastal objects. They are used to check the consistency of the semantic given to the region using the ontology. An experiment on an image of the Normandy coast (France) highlighted the benefits of the approach.

The main contribution of the paper is to present a formalization of the knowledge of the expert. We wanted to highlight that modeling and using expert knowledge could help improving the interpretation results. This method can only provide interesting results, if the initial labeling is not perfect. If the expert possesses a method to directly

Table 5: Confusion matrix before the application of the KFs

	Slikke	*Beach*	*Dune*	*Field*	*Wood.*	*Water*	*Building*	*Salt meadow*
Slikke	85133	111	1054	0	0	12714	9356	15
Beach	163	4201	775	0	0	0	2989	0
Dune	99	19	46347	13744	820	356	1319	1333
Field	223	0	3595	35096	3017	21	0	625
Wood.	0	0	1171	1932	5986	225	94	1005
Water	1003	0	35	12	190	7698	0	0
Building	892	254	1046	172	4	110	1753	185
Salt meadow	463	0	2364	1568	1101	39	58	10360

Table 6: Confusion matrix after the application of the KFs

	Slikke	*Beach*	*Dune*	*Field*	*Wood.*	*Water*	*Building*	*Salt meadow*
Slikke	95435	751	130	0	0	10909	219	939
Beach	1076	5092	644	119	0	0	1183	14
Dune	325	245	53084	8438	820	356	709	60
Field	223	0	3484	34984	3017	21	0	848
Wood.	0	0	2185	1415	5986	225	94	508
Water	1003	0	22	12	190	7698	0	13
Building	892	254	573	492	4	110	1505	586
Salt meadow	468	9	1057	49	0	39	44	14287

obtain good results, our approach is not interesting anymore. However, we carried out discussions with geographer experts and they have shown a strong interest in our method. Indeed, our method only uses simple knowledge and does not require direct examples, which are generally difficult to select in object-based classification. Moreover, a classifier can easily be created and used on different images without selecting new examples on each image. Using shapes and relationships between regions has been already explored (e.g. eCognition software). However, it is often difficult to link expert knowledge expressed in free speech and computer programs. In this paper, we explained how we used expert knowledge, and make it actionable to use for automatic image interpretation.

In future work, we plan to develop the ontology and to enhance it with more knowledge. For the moment, the ontology and the KFs are store separately. We would like to formally describe the knowledge represented by the KFs inside the ontology. We also plan to develop an OWL-DL version of the ontology to use a reasoner to automatically discover mislabeled regions. Furthermore, we also would like to evaluate the benefit of using an optimization approach in the step of consistency checking. Indeed, the current iterative algorithm does not ensure the discovery of a global maximum. However, as the search space might be huge (the number of region $\times$ the number of classes), meta-heuristic approaches might be considered. We are also considering increasing the interaction with the expert during the interpretation of the image and request feedback on the decision of the method in order to guide the process.

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