Ontology based interpretation of Very High Resolution imageries – grounding ontologies on visual interpretation keys

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Abstract

Object-based image analysis (OBIA) approach is an accepted and efficient method for classifying very high resolution (VHR) datasets. The classification process relies on the knowledge and experience of the expert conducting the classification. Therefore, the classification task is an error-prone and time-consuming process. To overcome this issue, this paper suggests a framework for ontology-based classification of image objects in VHR imageries. In particular, the paper focuses on the challenges associated with the ontology development, the so-called ontology-grounding problem. We test the feasibility of visual interpretation keys (VIKs) to extract information from VHR data. The ontology models the VIKs used to extract information from VHR imageries and match this information with application domain knowledge that triggers the image interpretation task. The benefit of this approach lies in the explicit specification of the knowledge used to extract information from satellite imageries.
Keywords: ontology, satellite imagery, OBIA, visual interpretation keys.

1 Introduction

In the last decade, Object Based Image Analysis (OBIA) has been accepted as an effective method for classifying high resolution datasets [1]. This image analysis method is an iterative approach that starts with the partition of the image into homogeneous units according to some pre-defined homogeneity criteria [1]. Created image objects become the analysis units for the subsequent image classification [2]. So far, the OBIA method is 'fully controlled by the experts' [3]. Therefore, the classification accuracy and the time spent on the image analysis task depend to a higher degree on the expert knowledge and experience about the spectral behaviour of real world objects, the interrelations between them and the embedding context. This constraint impedes the usefulness of OBIA in operational frameworks where "the speed and flexibility with which information is produced is an important factor" [4]. To solve this problem, we need to specify the a priori knowledge used to extract information from satellite imageries into consistent models and to make these models intrinsic to the image analysis systems.

The present work is an on-going research dedicated to the development of a methodological framework for ontology-driven object recognition from optical remote sensing data. In this paper, we focus on the challenges associated with the ontology development, the so-called grounding of ontologies problem [5]. According to [5], 'the claims of any domain theory need to be based on some observations in that domain'. We 'ground' our ontology on the visual interpretation keys (VIK) usually used in the aerial photographs interpretation task as guidelines for the delineation of feature of interest. This is a plausible approach as the 'spatial resolution gap between VHR data and aerial photographs has decreased' [6]. The ontology models the semantics of the VIKs and matches this information with application domain knowledge that triggers the image interpretation task (image analysis goal). The following issues will be discussed in this paper: (1) ontology and satellite imagery interpretation in the OBIA context; (2) developing ontologies for imageries interpretation using expert knowledge modelled in the form of VIKs; (4) validation of the VIKs-based classification.

2 Ontology and image interpretation in the OBIA context

The ontology is defined as "formal, explicit specification of a shared conceptualization" [7]. It captures the semantics of the domain concepts into knowledge organization systems that can be easily reused and extended. In remote sensing, the ontology is seen as a solution to reduce the semantic gap between digital information (*Digital Numbers* -DN) measured in the satellite imageries and the knowledge used to give meaning to the low level image information [8]. Ontology-driven image interpretation makes sense especially in the OBIA context where the image objects together with their spectral characteristics, morphological properties (shape, size etc.) and the spatial context become the units of analysis in the image interpretation procedure. By contrast, the pixel-wise approach uses the pixel spectral reflectance as the building blocks of image classification. Few research works focused on the ontology as solution to enhance the image interpretation [9-11]. These approaches offer solutions for matching image objects against the concepts whose semantics are modelled in the ontology. To generate the Knowledge Base (KB) used for the scope of classification, the authors are applying mainly machine learning techniques. Therefore, the resulting KB is tailored to a specific area, the robustness of the resulting classification being reduced. In our research, we are interested in increasing the transferability of the image classification.

3 Methodology

3.1 General framework for implementing ontology-based recognition of objects from remote sensing imageries

This work is part of a general ontology-based framework used to classify objects extracted from satellite imagery. The framework builds upon semantic web technologies and OBIA methods. OBIA is used to partition the image into discrete objects and to compute the image object attributes (called in this paper features) which are relevant for the classification purpose.

At the core of our methodology there is an ontology-based reasoning layer serving as mechanism for matching features of image objects against the application domain concepts. The image objects delineated applying available segmentation algorithms are exported in the GeoJSON format and used as input dataset for the subsequent classification. The *a priori* knowledge is explicitly modelled in the ontology using Web Ontology Language2 (OWL). The system itself has been developed in Java and consists of several modules including a reasoning system (Pellet API), GeoJSON, OWL API (http://owlapi.sourceforge.net/), WordNet API (http://lyle.smu.edu/~tspell/jaws/index.html) and KML API. In this paper we focus on ontology grounding problem.

3.2 Developing ontologies for image interpretation

Image analysis and interpretation require the following knowledge [12]: (1) application domain knowledge; (2) image analysis knowledge. Therefore, an ontology-based image interpretation framework needs to account for these two knowledge bases (Figure 1). Domain knowledge refers to the domain terminology whose underlying semantics are modelled in the domain ontology. The knowledge used for image interpretation is divided into qualitative knowledge and quantitative information. Qualitative knowledge refers to the spectral and spatial behaviour of objects of interest in the VHR imageries described by natural language terms (qualitative information): e.g. vegetation has a high Normalized Vegetation Index (NDVI); rivers are elongated. This qualitative knowledge is linked to image information (image object features computed using available algorithms).

A critical step in the ontology engineering process is the development of a KB that reflects the domain semantics at a specific granularity (level of details). This problem is known as the ontology grounding problem [5]. In our work, application domain vocabulary was derived from the UN Land Cover Classification System (LCCS) [13], while the image features used to assign the image objects to the corresponding class are elicited from existing VIKs. We aim at developing a generic image analysis model that can be reused in similar image analysis contexts. Therefore, the classification robustness is an important criterion for defining real world classes to be identified in the image.

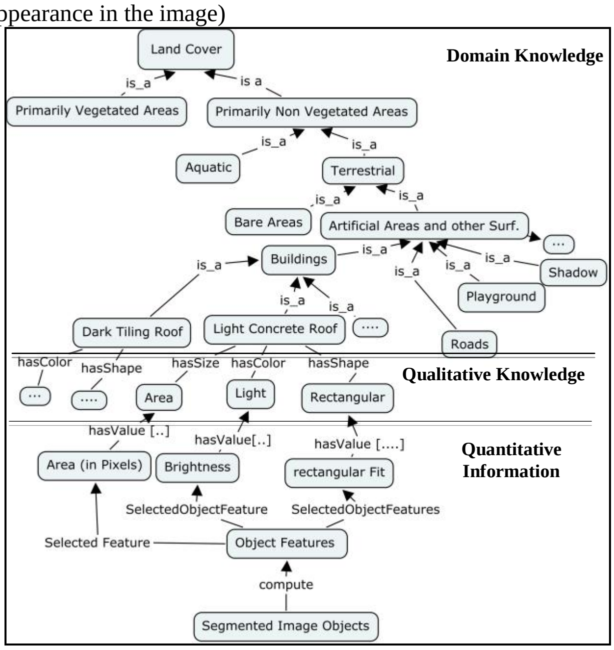
A) Application domain knowledge

Application knowledge can be gathered from existing classifications, different text corpus or by interviewing the experts. In this particular case, we extended the UN LCCS with the following classes identifiable in the VHR data: (1) buildings; (2) Roads/ParkingLots; (3) water bodies; (4) playgrounds; (5) shadows; (6) vegetation. The shadow class was introduced to avoid the confusion between shaded objects and other classes with similar spectral reflectance, i.e. water or dark-roofed buildings.

B) Image Interpretation knowledge

In OBIA, the objects of interest are classified based on the expert knowledge and experience about spatial and spectral behaviour of real objects in the VHR data [14]. The challenge is to find the relevant features to define the classes. To achieve this, we employed VIKs designed to interpret aerial photographs as reference knowledge to identify objects of interest in the imagery (Table1).

Figure 1: Excerpt of developed ontology. Domain Knowledge conveys the domain nomenclature and underlying semantics, whereas Qualitative Knowledge and Quantitative information accounts for the image analysis knowledge (image objects appearance in the image)



The idea of VIKs for VHR interpretation is not a novel approach [6] and [15]. However, to our knowledge, none of the existing ontology based image interpretations applied this solution to overcome the problem of the ontology-grounding problem.

3.3 Knowledge formalisation

The formalization of land cover classes semantics relies on the last advances of semantic web technologies. So far, there is a plethora of knowledge modelling languages relying on different modelling formalisms. In this work, we are using Ontology Web Language2 (OWL2) specifications. This language is a World Wide Web Consortium (W3C) recommendation.

Table 1: Excerpt of the interpretation keys used to describe individual classes to be extracted from satellite imageries (Source [12], sample and image descriptors added by authors)

Class	Sample	Colour, Shape, Size	Image Descriptor
Vegetation		Green, different shape	NDVI
Tiling Roof		Dark brown, Rectangular shape	Red/Green Ratio Density; Area
Light concrete roof		White, Rectangular shape, variable size	Brightness Density; Area
Asphalt street		Dark grey, Elongated shape narrow	Elongation
Playground		Orange rectangular shape	Red/Green Area

The OWL2 semantics allow us to express restrictions to a range of data values, to model low-level image information and to link it with the application domain concepts in the ontology.

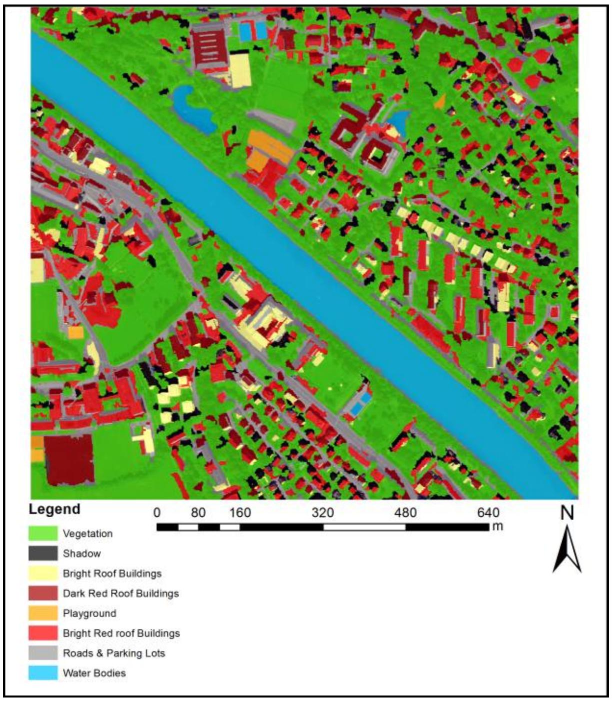
3.4 Classification testing and first results

We test the feasibility of the selected VIKs through a use case scenario dedicated to the extraction of buildings, Roads/ParkingLots, playground, water bodies and vegetation from WorldView2 (WV) imagery. The study area is located in Salzburg city, Austria (2071*1917 extent). WV is the first high-resolution eight-band, multispectral commercial satellite collecting multispectral imagery at 1.8-meter resolution and panchromatic imagery at 0.46 meters (Digital Globe, Inc. - http://www.digitalglobe.com). The WV imagery was segmented into homogeneous image objects using multi-resolution segmentation algorithm [16] implemented in eCognition software package (http://www.ecognition.com/). We visually examined the quality of the segmentation outputs and refined them by using spectral difference segmentation algorithm. The non-vegetated areas were masked out using NDVI index, whereas water body class is identified using Normalized Difference Water Index (NDWI) (equation 1):

$$NDWI = \frac{(\text{Green} - \text{NIR } 1)}{(\text{Green} + \text{NIR } 1)} \tag{1}$$

The remaining classes are classified using the class descriptors displayed in Table 1. The morphological characteristics (shape, size etc.) play an important role in class definitions especially when dealing with complex urban environments [17]. The following shape metrics were used: area, density feature defined in eCognition software package as the number of object pixels divided by its approximated radius and the elongation feature.

Figure 2: Classification results of the study area (subset of Salzburg city, Austria) yielded by translating the VIKs into classification rulesets.



The classification results (Figure 2) were assessed using a standard confusion matrix [18]. The reference samples were created through the visual interpretation of the stratified samples using Bing Map Aerial (©2012 Nokia, © 2013 Microsoft Corporation). The generated confusion matrix (Table 2) assess the thematic accuracy of the finer concepts classified based on the image descriptors depicted in Table 1. The classification achieved an overall accuracy of 82% and a kappa index of 0,77.

Table 2: Accuracy assessment of the classification. The bright roof buildings, dark red roof buildings and bright red roof buildings classes were merged into a single class ('Buildings' class) Samples – number of samples per class; PA % - Producer's Accuracy; UA%- user's accuracy

	Vegetation	Buildings	Playground	Roads& ParkingLots	Water Bodies	Shadow	Samples	PA (%)	UA (%)
Vegetation	41	1	0	0	0	1	43	74,55	95,35
Buildings	0	45	0	4	0	4	53	73,77	84,91
Playground	0	0	8	0	0	0	8	100	100
Roads & ParkingLots	3	10	0	41	0	1	55	91,11	74,55
Water Bodies	0	0	0	0	17	0	17	100	100
Shadow	11	5	0	0	0	33	49	84,62	67,35

4 Discussion and conclusions

In this paper, we described the ontology grounding phase involved in the process of ontology-based recognition of objects from satellite imageries. To select the relevant features for the class definitions, we used VIKs whose feasibility was tested through a use-case scenario presented in section 3.4.

Since our goal was to develop reusable image analysis workflow, developed classification relied on spectral ratios, indexes and shape metrics. The image regions classification by means of indexes is independent of image distortions leading to DN values inconsistencies within the class. The shape metrics proved to be useful to classify classes with similar spectral reflectance: concrete streets vs. concrete roof.

The shape descriptions assume complete and contiguous objects [17] and therefore, their efficiency for the image object classification depends on the quality of the segmentation results. The use-case scenario showed that applied segmentation algorithms do not create always meaningful image objects that fit the asserted concept definition and thus challenges the development of automatic object recognition systems that requires: '*consistent pixel intensity, predictable shape and well-defined edges'* [19]. For example, the streets occluded by shadows were oversegmented (split into many segments) and the generated image objects were misclassified as buildings. Thus, the 'Roads and ParkingLots' class achieved the lowest user accuracy's: 74,5% (Table 2). The class 'Buildings' yielded the lowest producer's accuracy (73,7%) because of the overlap with the 'Roads and ParkingLots' and 'Shadow' class. The confusion with 'Shadow' can be however solved by assigning the shadow class to the 'Buildings' class using neighbourhood relations.

We concluded that the robustness and accuracy of the proposed methodology depends on the quality of the image segmentation which remains an open problem within OBIA [3]. To improve the segmentation results, ancillary data can be used (e.g. LiDAR data).

Despite the above presented limitations, the proposed framework may contribute to the development of operational image analysis frameworks where "*precision can be traded for robustness and computational efficiency*" [8].

The image processing knowledge is modelled in the ontology using the OWL2 specifications. OWL2 allows us to run reasoning on top of developed ontologies. Thus, implicit knowledge can be inferred based on the explicit knowledge conveyed in the ontology. The explicit specification of the underlying meaning of information extracted from VHR data extends the advantages of OBIA regarding the automatic integration of information extracted from satellite imagery with GIS data. Moreover, the ontology-based recognition of objects from satellite imageries is an important step towards overcoming the semantic heterogeneity problems. The achievement of semantic interoperability fits the requirements of the existing Spatial Data Infrastructure (SDI) initiatives such Global Monitoring for Environment and Security (GMES) and Global Earth Observation System of Systems (GEOSS).

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