Multi-agent Systems in Remote Sensing Image Analysis

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Abstract: With remote sensing data and methods we gain deeper insight in many processes at the Earth's surface. Thus, they are a valuable data source to gather geo-information of almost any kind. While the progress of remote sensing technology continues, the amount of available remote sensing data increases. Hence, besides effective strategies for data mining and image data retrieval, reliable and efficient methods of image analysis with a high degree of automation are needed in order to extract the information hidden in remote sensing data. Due to the complex nature of remote sensing data, recent methods of computer vision and image analysis do not allow a fully automatic and highly reliable analysis of remote sensing data, yet. Most of these methods are rather semi-automatic with a varying degree of automation depending on the data quality, the complexity of the image content and the information to be extracted. Thus, visual image interpretation in many cases is still seen as the most appropriate method to gather (geo-) information from remote sensing data. To increase the degree of automation, the application of multi-agent systems in remote sensing image analysis is recently under research. The paper present summarizes recent approaches and outlines their potentials.

1 INTRODUCTION

Remote sensing data is a valuable data source for a variety of disciplines related to Earth's surface and the environment. With it, fast and even ad hoc maps can be produced (e.g. for hazard management) or long-term processes and their footprints can be monitored (e.g. the ongoing deforestation, the global urbanisation or the desertification). Further, archives of remote sensing data are growing continuously (Ma et al. 2015). In this context, terms such as "digital Earth" (Boulton 2018) or "Big Earth data" (Guo 2017) evolved recently. However, in comparison to other types of image data, particularly remote sensing data are very complex to handle due to their complex contents and characteristics. Thus, in many cases, human image interpretation is understood as the most reliable method to extract geo-information from remote sensing data. However, manual mapping from remote sensing data needs a lot of experience in image interpretation and is very labour intensive. The results of manual image interpretation are subjective and of limited reproducibility. However, automatic methods producing comparable results as human image interpretation does, are not in sight yet.

Recent automatic methods must compromise between the degree of automation and the accuracy and reliability of the results. The higher the level of detail and accuracy, the more individual imaging situations must be considered. This, in turn, increases the complexity of the rule sets and algorithms applied, which simultaneously reduces their robustness and general applicability. This dilemma has been asserted already by Hofmann et al. (2011), Rokitnicki-Wojcik et al. (2011), Kohli et al. (2013) and Anders et al. (2015). Current strategies to increase the degree of automation follow a design pattern approach as it is known from engineering: By developing so-called "master rule sets" for similar problems individual results are produced by deviating a specialized solution for individual images (Tiede et al. 2010). However, depending on the complexity of the mapping task and the data used, the human effort with these approaches is still relatively high. Thus, to efficiently exploit the ever-growing remote sensing and geo-data archives the degree of automation in image analysis must increase. That is, automatic remote sensing image analysis must become more flexible and robust against perturbations, similar the way human visual image interpretation is already.

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Research in remote sensing image analysis traditionally investigates the potential of AI methods – mainly those of computer vision. Investigating agent-based methods could foster the degree of automation and reliability in this particular field, since automating the analysis of remote sensing data is less a computer vision problem but rather a problem of optimally apply, network and parameterize known methods of computer vision and image processing. A key role in this context plays knowledge and knowledge description: while for visual image interpretation so-called “interpretation keys” are used, which verbally describe how the objects of interest look like, in computer based image analysis domain specific knowledge, knowledge about the data’s genesis and knowledge about sensible methods to process the data is incorporated the one or other way (e.g. Belgiu et al., 2014; Arvor et al. 2013). Once made explicit, e.g. as a formal ontology, this knowledge can be used as rules, rule sets and/or algorithms for image analysis. Nevertheless, knowledge often is also incorporated implicit, too, e.g. by Artificial Neural Networks (ANNs) or by other sample based classification methods. Independent of its representation, this knowledge is often distinguished into: *declarative knowledge* which describes the characteristics of the expected object-classes and *procedural knowledge* which describes the necessary image processing methods. Accordingly, recent agent-based methods of image analysis can be roughly separated into two types: methods which operate at procedural level and try to adapt existing methods similar to the design pattern approach and methods which operate at descriptive level and try to optimize the objects’ representation in the image, that is, their delineation. However, applying agent-based methods for remote sensing image analysis is still at its beginning and has a lot of potential which goes beyond the improvement of image analysis. The paper present tries to outline the state of the art in this particular field and its potential for future applications.

2 REMOTE SENSING IMAGE ANALYSIS

While visual image interpretation of remote sensing data is still a common way to gather information from remote sensing images, at least since the 1970ies there were always attempts to automate image analysis (e.g. Colwell, 1968). Until the millennium Landsat images with a resolution of 30m were the dominating set of optical Earth Observation (EO) data. Thus, for the most applications it was sufficient to analyse images based on the radiometry and its statistics stored in single pixels. Before the millennium, higher spatial resolution could only be achieved with airborne data, but from 2000 onwards the resolution of space borne data increased from 1m to 0.3m in 2010. Although with the new sensors more details were visually recognizable, automated image analysis of this kind of data became rather complex. It soon turned out that new analysis methods for Very High Resolution (VHR) remote sensing data were necessary. Thus, methods which operate on image segments (Object-Based Image Analysis, OBIA) instead of pixels and which incorporate formal expert knowledge became more and more popular (Benz et al. 2004; Blaschke 2010). Blaschke et al. (2014) were even speaking of a paradigm change in remote sensing image analysis.

In order to reuse once developed methods, workflows of individual image analysis can be noted, stored and re-applied the one or other way (often named rule sets). For this purpose, Domain-Specific Languages (DSL) comprising all necessary domain specific terms, rules and knowledge descriptions were developed (e.g. Schmidt et al., 2007). With these DSLs it is possible to develop individual solutions according to the design-pattern approach.

2.1 Pixel-based Image Analysis

In remote sensing many methods of pixel-based image analysis are applied. Some of them are specific from the remote sensing domain, such as the calculation of the Normalized Differential Vegetation Index (NDVI) and ortho-rectification, others are rather general, such as texture analysis based on the Grey Level Co-Occurrence Matrix (GLCM). For analysis purposes each pixel of an image is assigned to a meaningful real-world class, that is, pixels are classified by an arbitrary supervised or unsupervised classification method. Besides the original grey values, derivative pixel values such as the NDVI or GLCM values can extend the feature space for the classifier. The list of classification algorithms meanwhile ranges from simple threshold-based classifiers, clustering algorithms and Support Vector Machines (SVMs) to Fuzzy Classifiers, Bayesian Networks and ANNs.

Nevertheless, for a successful application of all these methods, a thorough knowledge of image processing and remote sensing is essential. That is, pixel-based image analysis usually consists of an (iterative) sequence of image processing methods which needs to be adapted according to the individual imaging situation (Lillesand et al. 2014; Canty 2014).

2.2 Object-based Image Analysis

In OBIA a (hierarchical) net of so-called image objects is generated by arbitrary image segmentations. With these image objects a lot of disadvantages which go ahead with the pixel-based approach for VHR remote sensing data vanish, such as the decreased signal-to-noise ratio in VHR data (the so-called "salt-and-pepper effect"; Blaschke and Strobl, 2001). A further recognized advantage of OBIA is its affinity to Geographic Information Systems (GIS): image objects aka image segments are very similar to polygons, which means many GIS-typical (polygon) operations can be used similarly with image objects. Additionally, GIS-polygons can be used for image segmentation and their attributes can be used in OBIA to support the classification.

Another advantage is the possibility to work with object hierarchies: Image objects at different segmentation levels represent pairwise disjoint objects of different size (i.e. at different scale). This approach reflects the multi-scale methods of landscape analysis and allows to develop semantic-rich rule sets for image analysis (Burnett and Blaschke, 2003; Stoter et al., 2011).

Further, the usable feature space in OBIA is of very high dimension: it comprises the objects' physical properties (colour, form and texture) and their semantic properties (hierarchical and spatial relations to other objects with certain characteristics and/or class memberships). Nevertheless, similar to pixel-based image analysis the whole process of analysing a single image can be very complex.

2.3 Knowledge Representation in Image Analysis

Pixel-based and object-based image analysis incorporate explicit and/or implicit knowledge for object identification. The knowledge used can be distinguished into two principle domains (Bovenkamp et al. 2004): *Procedural knowledge*, describes all image processing methods and parameterisations necessary to extract all intended object categories from the image data. If *procedural knowledge* is represented explicitly, it is described as so-called *task ontology*. *Declarative knowledge* describes the shape of the intended object categories, that is, how these classes appear in the image data similar to an image interpretation key but with measureable feature values and constraints. It can then be represented explicitly by a so-called *descriptive ontology* and used to automatically infer an objects class membership. Both knowledge domains are interlinked, as the following example demonstrates: vegetation can be easily identified in remote sensing data using the NDVI. The NDVI is commonly calculated by:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

Whereas *NIR* represents the grey value in the Near Infrared band and *Red* the grey value in the Red band of a sensor. A value of $0.0 < \text{NDVI} \leq 1.0$ indicates "vegetation", a value of $-1.0 < \text{NDVI} < 0.0$ indicates "no vegetation". The *declarative knowledge* which describes "vegetation" must represent this typical shape of vegetation by an appropriate (classification) rule, e.g.:

```
Class vegetation {
 …
   0.0 < NDVI(x) < 1.0;
 …
};
```

With `x` representing any individual pixel or segment of an image. The *procedural knowledge* for the class "vegetation" must include a description of how the NDVI is calculated (see eq. 1) with the data currently used, e.g.:

```
If sensor = "Landsat 8" THEN
   NDVI(x) = band 4(x) – band 3(x) /
   band 4(x) + band 3(x);
Endif.
```

The way how *procedural* and *declarative knowledge* are represented can be manifold. In the example given, it is noted explicitly and crisp. But it could be represented implicit and/or fuzzy, too. By noting this knowledge explicitly, e.g. as a formal ontology, it can be reused and/or adapted easily. However, implicit representations (e.g. as trained classifier or as a Convolutional Neural Network, CNN) are possible, too, but have a black-box character and are therefore less comprehensible and less adaptable.

3 AGENT-BASED METHODS IN IMAGE ANALYSIS

Applying agent-based methods in image analysis is relatively new. According to Rosin and Rana (2004) many methods of computer vision which claim to be agent-based are not. They often lack basic elements of agent-based computing, such as situation awareness, autonomy of individual agents, goal-orientation of agents, cooperation and communication of agents and many more. However, some recent agent-based methods of image analysis follow the agent-based paradigm (Jennings 1999; Wooldridge 1998). Especially in remote sensing, agent-based approaches for image analysis can be separated into two major types as outlined in section 1: *procedural level* approaches and *declarative level* approaches.

3.1 Approaches Acting at Procedural Level

In the very beginning of agent-based image analysis, Multi Agent Systems (MAS) were mainly used to parallelize necessary image processing tasks and to improve their performance (Lueckenhaus and Eckstein, 1997). Besides the potential for parallelisation of image analysis Lueckenhaus and Eckstein (1997) outlined the ability of software agents to be aware about their environment, to be able to cooperate, to be able to learn and plan, that is, to react flexible on a varying environment and to be goal-oriented. Thus, their agent-based system for image analysis went beyond a simple parallelisation of image analysis tasks. It rather enabled the MAS to autonomously organize all necessary image analysis procedures in order to optimize the results and the operating costs.

Zhou et al. (2004) followed this approach but aimed at an increase of performance and robustness of computer vision systems for real-time applications in dynamic environments. They organising the underlying MAS architecture like a Resource Management (RM) system, wherein software agents are negotiating processing priorities and resources according to the current situation of the system and its environment. Their system has been tested among others in remote sensing to reduce and optimize the downlink of satellites.

Heutte, et al. (2004) introduced a similar system for handwritten text recognition. But in contrast to the system of Zhou et al. (2004) this system incorporates knowledge at different levels. For each knowledge level an according group of specialised software agents was created, each of which being responsible for a dedicated task (e.g. for letter recognition or feature extraction).

Cellular automata (Liu and Tang, 1999) were another approach, primarily for image segmentation. Pixels aka cells or agents which meet certain homogeneity criteria were labelled and aggregated to image segments.

3.2 Approaches Acting at Declarative Level

Bovenkamp et al. (2004) introduced a MAS for segmenting Intra Vascular Ultra Sound (IVUS) images. By describing and applying *procedural knowledge* and *declarative knowledge* simultaneously. In their approach five different specialized types of segmentation agents, each of which responsible for the delineation of different object classes, plus a control instance responsible to dissolve conflicts were implemented and connected to a MAS. The MAS incorporates global constraints, contextual knowledge and local image information.

To the knowledge of the author Samadzadegan et al. (2010) were the first who applied agent-based methods in the remote sensing domain. Similar to the approach of Bovenkamp et al. (2004) they developed a MAS which consists of two groups of software agents to classify pixels in a Digital Elevation Model (DEM). The DEM has been deviated from a Light Detection And Ranging (LiDAR) point cloud and is represented as a 2D grid of cells. Within the groups, agents can apply dedicated procedures of image processing and reasoning in order to extract buildings and trees from the data. Conflicts occurring during the detection process are solved by a "coordinator agent". In both approaches, *declarative knowledge* has been applied for reasoning the class membership of each segment.

Mahmoudi et al. (2013 and 2014) were the first who combined agent-based methods with OBIA methods. For the purpose of mapping urban structures in WorldView-2 satellite data, they segmented the image using a global segmentation algorithm, here: the Multi-Resolution Segmentation (MRS) according to Baatz and Schäpe (2000), and then applied a MAS to assign the segments to classes. That is, reasoning agents used *declarative knowledge* for assigning each segment to according classes. However, by resigning agents being responsible for the segmentation or other sensible image processing operations, that is, agents acting at procedural level, this approach is relatively static.

Borna et al. (2014, 2015 and 2016) introduced an agent-based system which allows image objects in OBIA to dynamically change their shape depending on each individuals' appearance and spatial context ("elastic boundary"). However, their approach is very similar to that of Samadzadegan et al. (2010) and Bovenkamp et al. (2004), except that it uses image objects represented as GIS vector objects instead of pixels. The dynamics of the “elastic boundaries” are rather driven by general abilities each “vector-agent” (VA) has, than by the class assignment or intermediate classification results. That is, declarative knowledge has no impact on the VAs’ behaviour.

At the same time Hofmann et al. (2014, 2015 and 2016) presented a conceptual framework for Agent Based Image Analysis (ABIA) of remote sensing data. Main focus of their research was to mimic a human operator who would either adjust an existing rule set (design pattern approach) or manually correct the object delineation aka image segmentation. They developed two types of independent MAS: (1) a MAS consisting of so-called Rule Set Adaptation Agents (RSAAs) and one or more Control Agents (CAs) to autonomously adapt given rule sets, and (2) a MAS of hierarchically organized Image Object Agents (IOAs) which can autonomously adapt their segment-boundaries (Fig. 1).

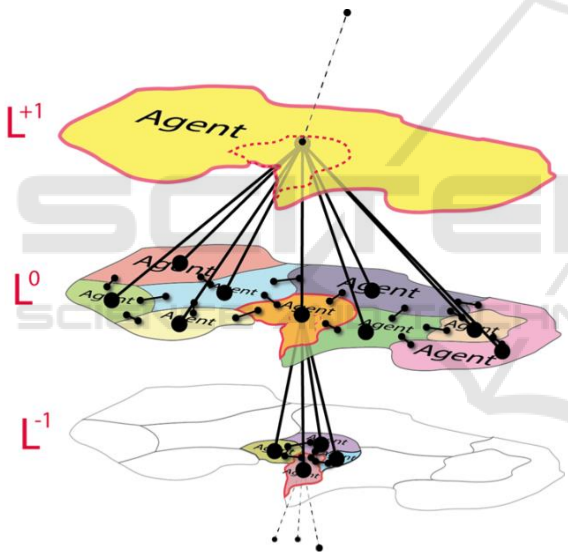

Figure 1: Hierarchy of Image Object Agents (IOAs).

Parts of the latter approach were further extended in (Hofmann, 2017) by a fuzzy Belief Desire Intension (fBDI) model which allows each IOA to decide in a fuzzy manner which is its next intended action.

Troya-Galvis, et al. (2016, 2018a and 2018b) investigated an approach to optimise image segments by means of controlling their classification quality through software agents. Similar to the approach of VAs in Borna et al. (2014, 2015 and 2016) and of IOAs in Hofmann et al. (2014, 2015 and 2016) this approach incorporates *declarative knowledge* to trigger software agents in order to improve each individual segment. After an initial segmentation, software agents can negotiate ambiguously classified or unclassified pixels in order to improve the segments’ classification quality. To avoid deadlocks, the segment-optimisation is applied cascaded and starts randomly. A control instance evaluates the achieved quality and triggers potential further segment adaptations.

4 AGENT-BASED MODELLING AND AGENT-BASED IMAGE ANALYSIS

Agent Based Models (ABMs) and recent agent-based image analysis of remote sensing data are relatives. ABMs have a long tradition in GISciences and other disciplines to simulate complex processes. First ABMs were applied in the late 1980ies and early 1990ies, e.g. Holland and Miller (1991) in economics or Huston, et al. (1988) in ecology. Major purpose of ABMs in GISciences is to simulate and explain complex spatial processes, that is, (1) to understand spatial patterns and how they are generated by interacting individuals and (2) to understand spatial and temporal interrelationships between individuals and their environment. All ABMs have in common to simulate the (spatial) behaviour of individual agents and the emerging spatial patterns based on relatively simple rules of (inter-) action with or within their environment. In doing so, it does not matter whether individual agents are spatially represented by simple pixels aka cells, or by GIS vector objects, that is, points, lines or polygons. Especially vector objects can be of arbitrary geometric (and dynamic) complexity; e.g. VecGCA, introduced by Marceau and Moreno (2008), allows agents being represented as polygons and to change their shape during simulation very similar to the approach of Borna et al. (2014, 2015 and 2016). However, in almost all cases remote sensing data has been used to validate the developed ABMs by comparing the observable patterns in remote sensing data with those produced by the ABMs (Adhikari and Southworth, 2012; Sohl and Sleeter, 2012; Megahed et al., 2015).

4.1 Similarities between ABM and Agent-based Image Analysis

Comparing the concepts of spatially acting agents in the remote sensing domain with the principles of ABMs, in both domains individual agents operate dynamically in space. However, while ABM agents generate spatial patterns, their counterparts in image analysis try to optimize the representation of real-world-objects by image segments. In both domains their behaviour is based on relatively simple rules noted in a Belief Desire Intention (BDI) model and the agents' perception of the environment. Since in both domains software agents represent spatial entities aka real-world-objects, the agents' BDI model depends on the real-world-objects they represent: The *procedural knowledge* for delineating "trees" in an image is different to that for "buildings". The same holds for their *declarative knowledge* to reason their class assignments. In a sensible ABM "tree"-agents certainly behave different than "building"-agents, which means their roles and abilities in an ABM are different. That is, the same real-world-objects are represented by two different kinds of agents, which exist and act in different environments, namely an image of the real world consisting of numerical values (remote sensing) and an abstract geometric model of the real world (ABM). In both representations, their behaviour is determined by the ontology of the real-world-objects they represent but it depends on the environment they act in.

4.2 Differences between ABM and Agent-based Image Analysis

The very difference between ABMs and agent-based image analysis concepts is the absence of robot-like agents in ABMs which are able to autonomously apply *procedural knowledge* in terms of selecting, combining or manipulating image processing methods.

Another difference is the agents' goals: in agent-based image analysis agents intend to achieve a best possible delineation of the imaged real world objects according to the *declarative knowledge* by applying *procedural knowledge*. The goal of agents in ABMs instead is to achieve an equilibrium or a Pareto optimality in the simulated (real-)world they are acting in.

A further difference is the absence of control instances in ABMs. In agent-based image analysis they are necessary to evaluate (intermediate) results during processing and to trigger the behaviour of individual agents. In ABMs such a mechanism is not necessary.

Further, in contrast to agents in ABMs, VAs or IOAs can change their class membership (and consequently change their behaviour): During the adaptation process it might happen, that individual IOAs or VAs fulfil the *declarative* criteria of multiple real-world-classes (simultaneously). ABM agents in principle only change their class or role explicitly by design.

Last but not least ambiguity in agent-based image analysis must be taken into account the one or other way. Even classification results can be ambiguous. In ABMs ambiguity only matters for the perception of the environment, that is, an agent's role in an ABM is unambiguous.

5 CONCLUSIONS AND OUTLOOK

The increasing growth of remote sensing data archives demands new methods of automatic, reliable and autonomous extraction of geo-information from remote sensing data. Recent methods are either lacking a high degree of automation or a high degree of reliability. Although recent methods of computer vision, such as CNNs are meanwhile very successful in diverse imaging domains, in the remote sensing domain they are not more suitable than other established methods.

Although not exhaustively researched yet, multi-agent systems for remote sensing image analysis have the potential to increase the degree of automation and reliability of remote sensing image analysis. Especially their ability to react flexible and robust on changing environmental situations (slightly changing imaging conditions, atmospherical impact, slightly changing image quality, seasonal impacts, etc.) seems to be promising. Nevertheless, research results which could confirm the advantage of agent-based image analysis methods especially in the context of analysing large archives are still missing. Troya-Galvis, et al. (2016, 2018a and 2018b) observed in their investigations slightly improved classification results compared to a CNN-based and a hybrid segmentation-classification approach called "Spectral-Spatial Classification" (SSC). Borna et al. (2014, 2015 and 2016) and Hofmann et al. (2014, 2015 and 2016) could just demonstrate the feasibility of their approaches, yet, but validation results, or results proofing the ability to reliably analyse large archives of remote sensing data are still missing. Last but not least enabling image analysis agents to learn (Biswas et al. 2005), especially for design pattern approaches, is an interesting aspect for further research. In this context the incorporation of implicit knowledge, in agent-based image analysis (e.g. by using ANNs) has not been investigated, yet.

From a geo-scientist's point of view, the similarity of ABMs and the concept of VAs or IOAs is a further interesting aspect: by coupling individual but corresponding ABM agents and VAs/IOAs, they could facilitate a quasi in-situ validation of an ABM simulation unlike the post-simulation validation, as it is still done today. The latter also has a high potential to improve our understanding of the environment and the Earth system, especially in conjunction with time series of remote sensing data. A further interesting aspect of coupling agent-based image analysis with ABMs is their consideration of scale: here hierarchically organized VAs/IOAs could support the validation of aggregation and emergence processes of individual agents in ABMs, such as urbanisation (de-)forestation or the evolvement of swarms.

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