International Journal of Multidisciplinary Research and Growth Evaluation.

Object based remote sensing image analysis using multi agents

Milind Deshkar [1*], **Dr. Manoj Kumar** [2]
[1-2] GLA University, Mathura, Uttar Pradesh, India

* Corresponding Author: **Milind Deshkar**

Article Info

ISSN (online): 2582-7138
Volume: 03
Issue: 03
May-June 2022
Received: 03-04-2022
Accepted: 19-04-2022
Page No: 57-61

Abstract
The earth's surface and crust contain a lot of valuable information and we can gain deeper insight using remote sensing data methods. The technology based on remote sensing and geospatial methods continues to increase the amount of data collected. We need effective strategies for data mining and image data retrieval, along with efficient methods of image analysis with a high degree of extraction of information collected from remote sensing data. The methods used for analysis are semi-automatic, which are unable to extract the required information from the complex remote sensing data, yet. With the use of object-based multi-agent systems in remote sensing image analysis, we can extract valuable information without affecting the crucial data collected. This paper summarizes and presents the recent multi-agents based technology and outlines their potential.

Keywords: Multi-agent systems, remote sensing, object based and agent based image analysis

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. ongoing deforestation, global urbanisation or desertification). Further, archives of remote sensing data are growing continuously. In this context, terms such as “digital Earth” (Boulton 2018) or “Big Earth data” (Guo 2017) [14] 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.

Hence, human image interpretation is understood as the most reliable method to extract geo-information from remote sensing data in many cases. 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.

The use of AI methods mainly those of computer vision are involved in remote sensing image analysis. Investigating agent-based methods could foster the degree of automation and reliability. The main role played is that of knowledge and its systematic description. For visual image interpretation “interpretation keys” are used, which verbally describe how the objects of interest use, computer-based image analysis domain-specific knowledge. Once made explicit, this knowledge can be used as rules and algorithms for image analysis. 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. There are two types of agent-based methods of image analysis: methods that operate at the procedural level and methods that operate at the descriptive level. The methods at the procedural level try to adapt existing methods similar to the design pattern approach. Whereas the methods at the descriptive level try to optimize the objects’ representation in the image, that is, their delineation. However, agent-based methods for remote sensing image analysis has a lot of potential that go 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

For most applications, it was sufficient to analyse images based on the radiometry and its statistics stored in single pixels. Before the millennium, the 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, image segment methods, like Object-Based Image Analysis, OBIA which incorporate formal expert knowledge became more and more popular 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 another way (often named rule sets). For this purpose, Domain-Specific Languages (DSL) comprising all necessary domain-specific terms, rules and knowledge descriptions were developed. According to the design-pattern approach, It is possible to develop individual solutions with these DSLs.

2.1 Pixel-based Image Analysis

Many methods of pixel-based image analysis are applied to remote sensing. 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. 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) [12].

2.2 Object-based Image Analysis

In OBIA a (hierarchical) net of so-called image objects is generated by arbitrary image segmentations. Using these techniques, many disadvantages of the pixel-based approach for VHR remote sensing data vanish. 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 sizes (i.e. at different scales).

The usable feature space in OBIA comprises the objects' physical properties (color, form and texture) and their semantic properties (hierarchical and spatial relations to other objects with certain characteristics and/or class memberships).

2.3 Knowledge Representation in Image Analysis

Explicit and/or implicit knowledge for object identification is incorporated for Pixel-based and object-based image analysis. The knowledge used can be distinguished into two principal domains (Bovenkamp *et al*. 2004) [10]: Procedural knowledge, describes all image processing methods and parameterizations 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 measurable feature values and constraints.

It can then be represented explicitly by a so-called descriptive ontology and used to automatically infer an object's 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:

$$\mathbf{NDVI} = \frac{\mathbf{NIR - Red}}{\mathbf{NIR + Red}}$$

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 $0.0 < NDVI \leq 1.0$ indicates "vegetation", a value of $-1.0 < NDVI < 0.0$ 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

According to, many methods of computer vision that claim to be agent-based are not. They often lack basic elements of agent-based computing, such as situation awareness, the autonomy of individual agents, goal- orientation of agents, cooperation and communication of agents and many more. 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. Besides the potential for parallelisation of image analysis 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. It 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) [22] followed this approach but aimed at an increase of performance and robustness of computer vision systems for real-time applications in dynamic environments. They organise 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.

3.2 Approaches Acting at Declarative Level

Bovenkamp *et al*. (2004) [10] introduced a MAS for segmenting Intra Vascular UltraSound (IVUS) images. 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.

Similar to the approach of Bovenkamp *et al*. (2004) [10] the author 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.

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 GI Sciences and other disciplines to simulate complex processes. First ABMs were applied in the late 1980ies and early 1990ies, e.g. Holland and Miller (1991) [16] in economics or in ecology. Major purpose of ABMs in GI Sciences 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. Vec GCA, introduced by, allows agents to be represented as polygons and to change their shape during simulation very similar to the approach of. 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) [1, 18].

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 behavior 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 differently 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 behavior 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 the 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 equilibrium or 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, we have to necessarily evaluate intermediate results during processing and trigger the behavior of individual agents. In ABMs such a mechanism is not necessary.

In agent-based image analysis, we have to necessarily evaluate intermediate results during processing and trigger the behavior of individual agents. In ABMs such a mechanism is not necessary. Also, as compared to agents in ABMs, VAs or IOAs can change their class membership and their behavior also: During the adaptation process many times, individual IOAs or VAs fulfil the declarative criteria of multiple real-world-classes (simultaneously). The ambiguity in agent-based image analysis must be taken into account one or other way.

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.

Multi-agent systems for remote sensing image analysis have the potential to increase the level 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. No research work is carried out in the field of agent-based analysis, especially in the context of analyzing large archives.

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) [6, 7, 15] 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.

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. 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 urbanization (de-)forestation or the evolvement of swarms.

6. References

1. Adhikari S, Southworth J. Simulating forest cover changes of Bannerghatta National Park based on a CA-Markov model: A remote sensing approach. Remote Sensing. 2012;4(10):3215-3243.
2. Anders NS, Seijmonsbergen AC, Bouten W. Rule set transferability for object-based feature extraction: An example for cirque mapping. Photogrammetric Engineering & Remote Sensing. 2015;81(6):507-514.
3. Arvor D, Durieux L, Andrés S, Laporte MA. Advances in geographic object-based image analysis with ontologies: A review of main contributions and limitations from a remote sensing perspective. ISPRS Journal of Photogrammetry and Remote Sensing. 2013;82:125-37.
4. Baatz M, Schäpe A. Multiresolution segmentation: An optimization approach for high quality multi-scale image segmentation. In: Strobl J, editor. Angewandte Geographische Informations-Verarbeitung XII. Wichmann Verlag, Karlsruhe; c2000. p. 12-23.
5. Belgiu M, Hofer B, Hofmann P. Coupling formalized knowledge bases with object-based image analysis. Remote Sensing Letters. 2014;5(6):530-538.
6. Benz UC, Hofmann P, Willhauck G, Lingenfelder I, Heynen M. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing. 2004;58(3-4):239-258.
7. Biswas G, Leelawong K, Schwartz D, Vye N. Learning by teaching: A new agent paradigm for educational software. Applied Artificial Intelligence. 2005;19(3-4):363-392.
8. Blaschke T, Strobl J. What's wrong with pixels?: Some recent developments interfacing remote sensing and GIS. GeoBIT. 2001;6(6):12-17.
9. Bovenkamp EGP, Dijkstra J, Bosch JG, Reiber JHC. Multi-agent segmentation of IVUS images. Pattern Recognition. 2004;37(4):647-663.
10. Burnett C, Blaschke T. A multi-scale segmentation/object relationship modelling methodology for landscape analysis. Ecological Modelling. 2003;168(3):233-249.
11. Canty MJ. Image Analysis, Classification and Change Detection in Remote Sensing: With Algorithms for ENVI/IDL and Python. CRC Press; c2014.
12. Colwell RN. Remote sensing of natural resources. Scientific American. 1968;218(1):54-71.
13. Guo H. Big Earth data: A new frontier in Earth and information sciences. Big Earth Data. 2017;1(1-2):4-20.
14. Hofmann P, Lettmayer P, Blaschke T, Belgiu M, Wegenkittl S, Graf R, *et al*. Towards a framework for agent-based image analysis of remote-sensing data. International Journal of Image and Data Fusion. 2015;6(2):115-137.
15. Holland JH, Miller JH. Artificial adaptive agents in economic theory. The American Economic Review. 1991;81(2):365-370.
16. Jennings NR. Agent-based computing: Promise and sensing image analysis. In: Proceedings of the 23rd International Conference on Pattern Recognition (ICPR); c1999. p. 829-34.
17. Sohl T, Sleeter B. Role of remote sensing for land-use and land-cover change modeling. In: Remote Sensing of Land Use and Land Cover. CRC; c2012. p. 225-40.
18. Stoter J, Visser T, van Oosterom P, Quak W, Bakker N. A semantic-rich multi-scale information model for topography. International Journal of Geographical Information Science. 2011;25(5):739-63.
19. Tiede D, Lang S, Hölbling D, Füreder P. Transferability of OBIA rulesets for IDP camp analysis in Darfur. In: Proceedings of GEOBIA 2010, Ghent, Belgium; c2010.
20. Zhou Q, Parrott D, Gillen M, Chelberg DM, Welch L. Agent-based computer vision in a dynamic, real-time environment. Pattern Recognition. 2004;37(4):691-705.