A Knowledge-Based System for Context Dependent Evaluation of Remote Sensing Data

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Abstract. Automatic interpretation of remote sensing data gathers more and more importance for surveillance tasks, reconnaissance and automatic generation and quality control of geographic maps. Methods and applications exist for structural analysis of image data as well as specialized segmentation algorithms for certain object classes. At the Institute of Communication Theory and Signal Processing focus is set on procedures that incorporate a priori knowledge into the interpretation process. Though many advanced image processing algorithms have been developed in the past, a disadvantage of earlier interpretation systems is the missing combination capability for the results of different - especially multisensor - image processing operators. The system GEOAIDA presented in this paper utilizes a semantic net to model a priori knowledge about the scene. The low-level, context dependent segmentation is accomplished by already existing, external image processing operators, which are integrated and controlled by GEOAIDA. Also the evaluation of the interpretation hypothesis is done by external operators, linked to the GEOAIDA system. As a result an interactive map with user selectable level-of-detail is generated.

1 Introduction

Knowledge-based image interpretation of remote sensing data offers a vast field of different applications, like automatic generation and quality control of geographic maps ([Gunst, 1996], [Englisch *et al.*, 1998]), environmental monitoring tasks like assessment of damage caused by clearing activities ([Hame *et al.*, 1998]) or natural disaster and also for surveillance of agricultural production. The rapidly growing number of multisensor remote sensing images enables several new applications, but also increases the labour-intensive manual evaluation of the data. This results in a growing demand for productive and robust techniques for (semi)automatic analysis and object extraction.

Previous analysis systems are often restricted to segmentation and classification of one or few different classes. They are highly specialized and optimised for a certain task or have difficulties processing large images. Especially methods which follow a strict structural approach ([Tönjes *et al.*, 1999], [Niemann *et al.*, 1990], [Kummert *et al.*, 1993]), i.e. they work with primitive objects extracted from the image data, are not capable of handling large, high-detailed aerial images due to the great number of extracted primitives in such images. Another typical problem of such systems is the visualisation of the analysis results. High resolution input images contain lots of small objects which can lead to confusing interpretation result maps.

The analysis system described in the following integrates already existing image processing operators which are intelligently controlled by utilization of previous knowledge about the processed scene. The previous knowledge is modelled by a semantic net. The net handles properties and relationships of different nodes. One property of a node could be the assignment of an existing *holistic* image processing operator which will be used for the detection of a certain object class. If an image processing operator for a particular task isn't available, the node will be identified *structurally* by its components, i.e. the child nodes.

As GEOAIDA transfers the segmentation task to external operators there is no limitation to the type of input images. Therefore multisensor scene analysis is also possible. Results of the scene analysis are displayed in an interactive map, which allows the user to select a task-adapted level of detail. The hierarchic map covers all results gathered during scene interpretation.

2 Functionality of GeoAIDA

Figure 1 shows the design of GEOAIDA (Geo Automatic Image Data Analyser).

On the input side the system consists of the components *database* and *semantic net*. Data processing is handled by *top-down-* and *bottom-up operators* which are called by the system control unit. Results are shown in an *interac-tive map* which consists of a *symbolic scene description* and *thematic maps*. The core system control queries the image database, reads the semantic nets as well as project descriptions and generates hypotheses by calling top-down operators. The hypotheses are evaluated with bottom-up operators and once verified, stored as instance nets with corresponding label images, which describe the position of the instance nets' nodes.

2.1 Database

The database provides all input information available for the scene interpretation. This includes images of different sensors, like VIS, laserscan, IR or SAR, as well as GIS Information or results of an earlier scene interpretation for multitemporal processing. GEOAIDA itself is not limited to any kind of input data restrictions are only imposed by the attached external image processing operators, which work on their dedicated input data. Internally GEOAIDA manages two dimensional regions which are assigned to nodes of the hypothesis or instance net.



Fig. 1. GEOAIDA design

2.2 Semantic net

The *a priori* knowledge about the scene under investigation is stored in a semantic net. The nodes of the net are ordered strictly hierarchical, i.e. each node has exactly one superior node. The topmost node is the scene node. Attributes can be assigned to each node. Common attributes are *name*, *class* and the associated *top-down* and *bottom-up* operators.

A top-down operator is capable of detecting objects of the node class in the given input data. For each detected objects a hypothesis node is generated. The bottom-up operator investigates the relationship between the subnodes and groups them into objects of the node class. These objects are represented by instance nodes. Top-down and bottom-up operators can also be configured by additional attributes, that are operator specific.

2.3 Top-down operators

Top-down operators (s. figure 2) are external image processing operators that run a segmentation on given input image data and assign the resulting objects to one or more classes. Additionally the operator is supplied with a binary mask which describes the areas of interest. If the native external operator doesn't handle masks, the masking is accomplished in a post processing step. Output of a *top-down* operator is a list of regions with a corresponding label image, which describes the position of the regions. Typical examples for such operators which are pre-registered with GEOAIDA are variance analysis for distinction of man-



Fig. 2. Operation of a top-down operator

made and natural objects, supervised texture segmentation, building extraction from laserscan data, etc..

2.4 Bottom-up operators

Bottom-up operators are used to group a multitude of objects to a smaller quantity of superior objects, s. figure 3. These operators are also implemented as external programs. Input of a *bottom-up* operator is a list of hypothesis nodes together with the corresponding label images, which describe the geometric position of the objects in the scene. The output is a list of instance nodes resulting from the grouping process and a new label image describing the superior objects.

2.5 Interactive map

The output of the GEOAIDA analysis is an instance net, which describes all verified objects of the scene. The ordering of the nodes is strictly hierarchical, i.e. the footprint of inferior (child) nodes is always completely represented in the superior (parent) node. Furthermore all nodes of the same hierarchic level are disjunctive. That means, that it is possible to describe the position of all objects of a whole instance tree in a two dimensional map.

Combination of the original semantic net with the instance net and the corresponding map leads to an interactive map. Opening and closing branches of the semantic or instance net changes the level of detail in the interactive map and improves the result evaluation for the user.



Fig. 3. Operation of a bottom-up operator

2.6 System control

Main task of GEOAIDA itself is system control. Analysis is accomplished in two major steps. First a *top-down* pass calling the attached holistic image processing operators generates hypothesis about the objects detectable in the scene. According to the semantic net these hypothesis are structured in the hypothesis net. The second step is a *bottom-up* progression through the hypothesis net. During this pass an instance net is generated from the hypothesis nodes on the basis of object properties like size, structural relationship between neighbouring objects, etc. The instance net together with the object map is the result of the two pass analysis.

3 Analysis example

In the following the functionality of GEOAIDA is illustrated with an example. Figure 4 shows a small excerpt of a multisensor aerial scene. Figure 4a is an orthophoto, figure is a 4b laserscan. Figure 4c to 4e are results of different holistic image processing operators, which were applied to the whole input image. Figure 4c was acquired by querying a geographic information system for street positions. With this information an initial region segmentation was executed. The laserscan image provides reliable data for building detection - the results are shown in figure 4d. Figure 4e shows the segmentation of a supervised texture analysis operator described by [Gimel'farb *et al.*, 1993].

All procedures deliver some special, detailed information about the investigated scene. However, none of them is capable of interpreting the scene in terms of land usage, as shown in figure 4f.



Fig. 4. a) ortho photo, b) laserscan, c) GIS segmentation, d) building extraction from laserscan data e) texture segmentation of ortho photo, f) final scene interpretation (1: forest, 2: industry, 3: forest, 4: unknown, 5: settlement)

At first a model of the scene has to be designed. The scene knowledge is modelled in a semantic net, s. figure 5. The actual shape of the semantic net depends on the desired result but also on the available image processing operators. The topmost node of the model is always the scene. In this example the scene consists of regions. These regions are initially determined by a GIS query ([Grünreich, 1992]). Regions on the other hand contain inhabited and agricultural areas. The differentiation between those two object classes can be achieved by evaluation of laserscan data. Areas with buildings are assigned to inhabited area, areas without to agricultural land. Beyond this a discrimination of inhabited areas into the classes settlement and industry is impossible for a simple image processing operator. GeoAIDA solves the problem by generating hypotheses for both classes. Segmentation of the laserscan data ([Steinle 1999]) produces hypotheses for houses and buildings. In parallel the system searches for gardens and parking areas with the help of the texture segmentation operator. After creation of hypotheses for all these subnodes the *bottom-up* operators of settlement and industry create hypotheses for themselves which are then propagated to the superior node 'inhabited area'. That node finds a final decision for the region subdivision based on probability ([Dubois et al., 1988]) and priority figures. The latter can be preset by the user or are generated during the analysis process respectively. In this example conflicts at the node 'inhabited area' are resolved by rating the objects in regard to size and compactness.

Due to the parallel execution of the semantic net branches, the agricultural areas have been segmented and classified as acreage, meadow or forest in the meantime. In this example the segmentation was carried out by one operator. Therefore the detected regions are already disjunctive. The *bottom-up* operator of the node 'region' gets the results of both branches and has to decide whether a region or part of a region is inhabited area or agricultural land. At this stage the initial region segmentation is verified. Existing regions can be splitted up or merged according to the analysis results. In the last step the new region partition is merged to the scene description.



Fig. 5. Model of a scene represented by a semantic net

Figure 4f shows the final scene interpretation result. Regions 1 and 3 have been identified as forest, area 2 is classified as industry because of the large buildings whereas area 5 is assigned to settlement. Area 4 is undetermined - no evidence for one of the modelled classes was found during the analysis course.

4 Conclusion

The knowledge-based, automatic image interpretation system GEOAIDA was presented. The functionality and features were demonstrated with an example application for land utilization. GEOAIDA uses a priori knowledge modelled by a semantic net together with two types of basic operators. Top-down operators segment and classify image data and produce probability and accuracy figures for the results. *Bottom-up* operators evaluate the hypothesis nodes generated by the top-down progression, solve classification conflicts and group the different object classes. The integration of external holistic image processing operators of different origin is easily accomplished. Due to the systems' capability of controlling holistic and structural analysis simultaneously it is predestined for the flexible classification of objects and regions in multisensor remote image data. A further extension of the application range of GEOAIDA is the possibility to incorporate previous knowledge of a geographic information system or earlier interpretation results of an investigated scene into the analysis process. Besides its flexible design for future research tasks GEOAIDA is a promising step towards productive use in image analysis and verification of geographic information systems.

References

- Bückner et al., 2000. J. Bückner, M. Pahl, O. Stahlhut, GEOAIDA A Knowledge Based Automatic Image Data Analyser for Remote Sensing Data, CIMA 2001, Second International ICSC Symposium AIDA, June 19-22, Bangor, Wales, U.K., 2001
- Dubois et al., 1988. D. Dubois and H. Prade, Possibility Theory: An Approach to Computerized Processing of Uncertainty, Plenum Press, New York and London, p. 263, 1988
- Englisch et al., 1998. A. Englisch, C. Heipke, Erfassung und Aktualisierung topographischer Geo-Daten mit Hilfe analoger und digitaler Luftbilder, Photogrammetrie Fernerkundung Geoinformation, Vol. 3, pp. 133-149, DGPF, Stuttgart, 1998
- Gimel'farb *et al.*, 1993. G.L. Gimel'farb, A.V. Zalesny, Probabilistic models of digital region maps based on Markov random fields with short and long-range interaction Pattern Recognition Letters, 14, pp. 789-797, 1993
- Grünreich, 1992. D. Grünreich, ATKIS A Topographic Information System as a Basis for a GIS and Digital Carthography in West Germany, Geol. Jb., Vol. A122, pp. 207-215, Hannover, 1992
- Gunst, 1996. M. de Gunst, Knowledge Based Interpretation of Aerial Images for Updating of Road Maps, Dissertation, Delft University of Technology, Netherlands Geodetic Commission, Publications of Geodesy, New Series, Nr. 44, 1996
- Hame et al., 1998. T. Hame, I. Heiler, J. San Miguel-Ayanz, Unsupervised Change Detection and Recognition System for Forestry, International Journal of Remote Sensing, Vol. 19(6), pp. 1079-1099, 1998
- Kummert et al., 1993. F. Kummert, H. Niemann, R. Prechtel and G. Sagerer, Control and explanation in a signal understanding environment, Signal Processing, Vol. 32, No. 1-2, May, 1993
- Niemann *et al.*, 1990. H. Niemann, G. Sagerer, S. Schröder, F. Kummert, ERNEST: A Semantic Network System for Pattern Understanding, IEEE Trans. on Pattern Analysis and Machine Intelligence, 12(9):883-905, 1990
- Steinle 1999. E. Steinle, H.-P Bähr, Laserscanning for change detection in urban environment Altan & Gründig (eds.): Third Turkish-German Joint Geodetic Days 'Towards A Digital Age', Volume I, pp 147 156, Istanbul, Turkey, ISBN 975-561-159-2 (Vol. I), 1999
- Tönjes et al., 1999. R. Tönjes, S. Growe, J. Bückner and C.-E. Liedtke, Knowledge-Based Interpretation of Remote Sensing Images Using Semantic Nets, Photogrammetric Engineering and Remote Sensing, Vol. 65, No. 7, pp. 811-821, July 1999