

Structural Interpretation of High Resolution Images

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Abstract— With increasing resolution of remote sensing data more and more details and structures of landscape objects are observable. An interpretation of such images requires the use of improved methods for object extraction. In this paper several approaches on this topic are presented. The basis of all approaches is an explicit knowledge representation with semantic nets. For different applications concept nets are shown and the strategy to use them. Furthermore a methodology to adapt the concept nets automatically to other resolutions is described and strategies to extend the methods to a multitemporal interpretation.

I. INTRODUCTION

Nowadays, the use of remote sensing data for creation of maps as well as their update is a standard procedure. Especially for map updating periods are defined, wherein the update has to be fulfilled. Depending on the object classes different update periods are defined. Due to the high amount of data and due to sometimes short update periods the automation of the extraction tasks is of interest.

The use of satellite images of lower resolution (e.g. Landsat TM) allows the extraction of particular object classes, which are large enough and hence observable in the images. Examples for such object classes are waters or forests. For most of these object classes the sole analysis of their spectral signature is sufficient, because that allows to directly infer the object classes.

During the recent years the resolution of the satellite images improved. Up to now satellite images are available with a resolution of several decimetres per pixel. With higher resolution the amount of observable object classes greatly increased. Now also smaller objects can be extracted from satellite images. But also the number of those object classes increased, which can not be extracted by using solely the spectral information.

Therefore the use of structural information about the objects becomes more and more important. Structural interpretation means the use of additional information about the objects for the interpretation procedure. This could be information about the parts, of which an object consists, about the shape structure, about the inner structure or about relations to other objects. Looking at different epochs a structural

interpretation means to use temporal semantic relations of the objects to improve the multitemporal interpretation.

In order to create an automatic interpretation procedure by using structural knowledge it is necessary to generate models for the object classes of interest. These models are called object models in the following. The models can be formulated in implicit or explicit knowledge representation languages. An explicit one has the advantage, that it can be understood by non experts as well, because it is formulated in standard language. The methods which are described in this paper use an explicit knowledge representation with semantic nets. The challenge in this area is to create suitable object models for different applications by using expert knowledge and to use them with a strategy for image interpretation. The generation of object models is usually done manually, but ongoing research tries to automate the procedure. Another challenge is the transfer of experts temporal knowledge about landscape objects into suitable models and their use for multitemporal interpretation.

In this paper several works within the area of structural interpretation from the research group of the author are presented. In section II some object models for different applications are presented, in section III a methodology to create object models automatically by an automatic adaptation to other resolutions and in section IV the extension of the described strategies to a multitemporal interpretation.

II. OBJECT MODELS

A. Knowledge Representation

There are several methods for the representation of object models. One kind is a representation by semantic nets [19]. Semantic nets are directed acyclic graphs. They consist of nodes and edges in between the nodes. The nodes represent the objects expected in the scene while the edges or links of the semantic net model the relations between these objects. Attributes define the properties and methods of nodes and edges.

The nodes of the semantic net model the objects of the scene and their representation in the image. Two classes of nodes are distinguished: the concepts are generic models of the objects and the instances are realisations of their corresponding concepts in the observed scene. Thus, the knowledge base,

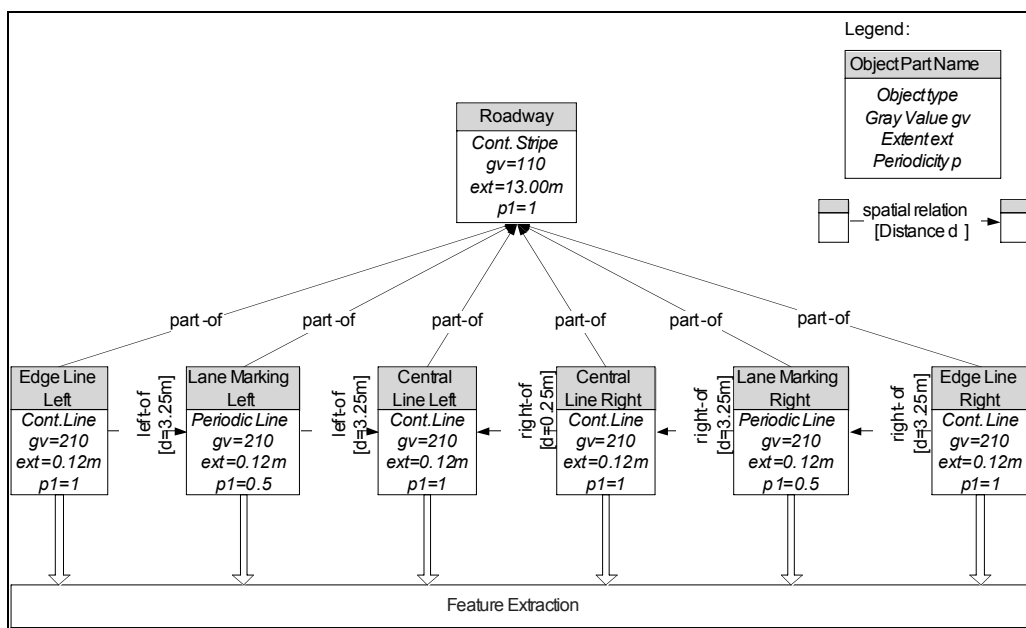


Figure 1. Concept Net for Dual Carriageway at Large Scale

which is defined prior to the image analysis is composed of concepts. During the interpretation a symbolic scene description is generated consisting of instances.

The relations between the objects are described by edges or links of the semantic net. The specialisation of objects is described by the is-a relation introducing the property of inheritance. Along the is-a link the description of the parent concept is inherited to the more special node which can be locally overwritten. Objects are composed of parts represented by the part-of link. Thus, the detection of an object can be simplified to the detection of its parts. The transformation of an abstract description into its more concrete representation in the data is modelled by the concrete-of relation, abbreviated con-of. This relation allows for structuring the knowledge in different conceptual layers, for example a scene layer and an image layer.

B. Interpretation System

For object extraction the knowledge-based image interpretation system GeoAIDA is used, which was developed at the Institute of Information Processing at the Leibniz University Hannover. It represents a tool for image analysis incorporating a priori knowledge in form of semantic nets [3] [4] [12]. It is a further development of the system AIDA, which was developed before at the same Institute [13] [26]. Hypotheses for the existence of object parts in the semantic net are generated and evaluated in the extraction process. GeoAIDA applies top-down- and bottom-up-operators. After generating the hypotheses, for each object part the corresponding top-down-operator (i.e. the assigned feature extraction operator in the semantic net) is called, extracting from the input image data the respective object part. The output of the top-down-operators is then evaluated and grouped to superior objects by the bottom-up-operators.

C. Use of Object Models for different Applications

The automatic extraction of roads is one of the big challenges in the area of image analysis and subject of ongoing research. Several approaches were published with different object models for the extraction of different types of roads in different scales. Examples for such approaches are [2] [9] [27] [32] [34]. One example for the use of semantic nets for this task is described in [8] [20]. The object model is depicted in Figure 1. In this example a dual carriageway is described by its road markings and the distances between them for the interpretation of high resolution images (3cm/pel). The extraction of a dual carriageway is simplified to the extraction of its road markings. At the bottom of the semantic net feature extraction operators [25] are connected to the nodes in order to extract the road markings. The main topic of this work was not the extraction of roads, it was the scale adaptation of road models (see section III). That is the reason, why the used object model is simple. But the results of the approach show that the model works. For further information see [8].

Many objects, especially man-made-objects, can be modelled by describing their parts, of which the objects consist. By contrast for many vegetation areas it is not possible, to define exact parts, which have to be found. They hardly ever show particular shapes or a homogenous texture. Nowadays this group of objects and areas is manually interpreted. So-called interpretation keys are often used for manual interpretation. They describe characteristic features or structures for different object classes, which have to be found for a correct classification. The existing approaches for automatic interpretation of vegetation areas mostly use only multispectral classification methods e.g. [18] [23] [30]. This is in many cases too simple, because many vegetation classes consist of different object parts with different spectral signatures. This strategy therefore fails for many vegetation areas, especially for many biotope areas.

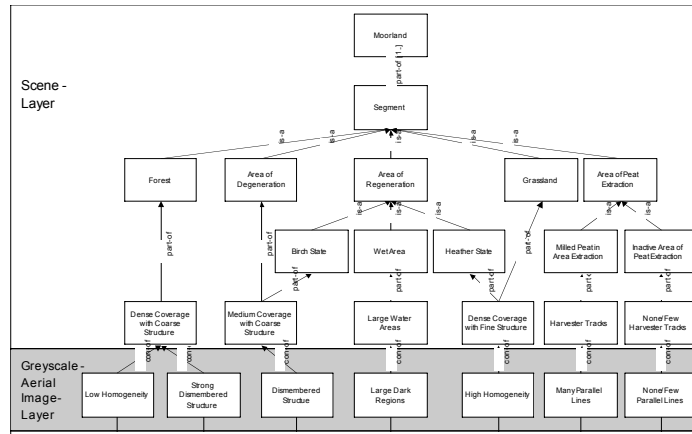


Figure 2. Concept Net for the Interpretation of Moorland

A possible strategy for such areas is based on the described manual approach, which applies interpretation keys and finds necessary features and structures for a class. Therefore the goal was to transform the interpretation keys into an object model and to use them for the automatic interpretation.

This was done in the approach [21]: Figure 2. shows an object model for the interpretation of a special kind of vegetation area: Moorland. The object model was created by representing the different classes by their features, which are given by interpretation keys. For the computation of the features particular feature extraction operators are used, which search within given segment borders for the features described by standard language. If for instance there is an operator which has to find harvester tracks, this operator searches for parallel lines within the given borders. Therefore in contrast to the interpretation of objects with a particular shape, spectral signature or texture, the interpretation of vegetation areas as in

Figure 2. requires a segmentation before the interpretation, because the feature extraction operators need segment borders, whereas in the object model in Figure 1. the operators are able to search for the road markings in the whole image.

Within the research area of vegetation interpretation the interpretation of agricultural areas is of enhanced interest. One application is the EU control mechanism MARS (Monitoring Agriculture with Remote Sensing) for crop prediction. Also insurance companies are interested in observation of such areas, e.g. for the documentation of damages caused by the weather (storm losses).

The first important approaches in the field of agricultural areas investigated the use of different indices in order to derive crop specific information [1] [7] [24] [28] and particular crop parameters [5] [11]. Different approaches deal with the recognition of crop classes in agricultural areas, e.g. [16] [29].

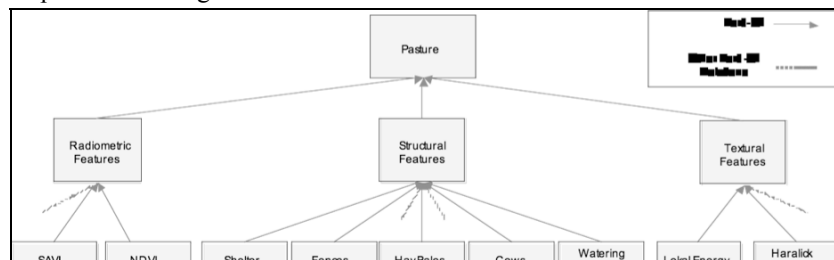


Figure 3. Concept Net for the Interpretation of Agricultural Areas

These approaches usually work only with spectral information, not with structural. Therefore the potential of the interpretation results are limited.

Figure 3. shows an example for a model, which uses structural information, here for the class pasture. In contrast to the concept net in Figure 2. the different types of information, which are derived from the images, are distributed into three groups: radiometric, textural and structural features. The computation of the radiometric features is geared to the known indices, which are used in many approaches within this topic. The textural features are computed in the way, which is known in literature for texture parameters (e.g. Haralick).

The third and most important type of feature is the structural feature. As described above also here interpretation keys were used to develop them. Examples for structural features are tracks from agricultural machines, bales of straw or cows. Figure 4. shows some structures, which give hints for the interpretation and thus are included in the interpretation process through structural features.

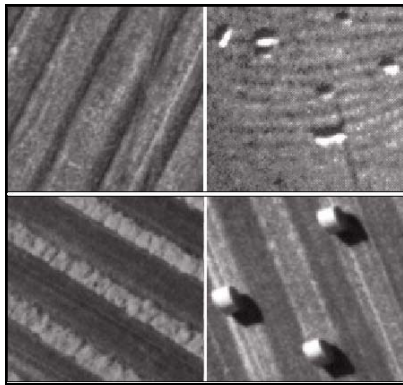


Figure 4. Structures in Agricultural Areas

III. AUTOMATIC SCALE ADAPTATION OF OBJECT MODELS

In the last section different examples for object models were shown. These object models were created manually by utilising the knowledge and the experience of human experts. It is important to consider that these object models describe landscape objects in digital images, but the appearance of them in the digital images depends on their spatial resolution. While many object details are visible in high resolution images, in low resolution images many of them disappear or merge. Where in high resolution images areas are observable, in low resolution images lines or even points might be found. This fact also affects an automatic extraction of landscape objects from digital images with different resolutions. The models for the same objects have to be different depending on the resolution of the images. They are tailored to specific scales of aerial and satellite images. Existing approaches for explicit object models did not permit an automatic transfer to other scales. Hence, a new model must be developed for each image scale manually. Based on the fact, that with lower spatial resolution, new details of objects will not appear, but existent details will more and more disappear, the object representation in image data of lower spatial resolution can be predicted

starting from high resolution. A methodology for an automatic adaptation of object models to lower spatial resolutions would make the manual generation of these object models for different resolutions redundant. Thus, a once created object model could be utilised for a wider range of applications and for diverse sensor types exhibiting a wider range of image scale.

In [20] exactly such a methodology was developed: a methodology to derive object models for low resolution images from models created manually for high resolution images. The approach was based on diverse researches in the area of scale-space and scale-space theory [6] [10] [14] [33].

Figure 5. gives an overview of the proposed strategy for scale adaptation. The main input of the process is a manually created object model, represented as a semantic net, with the description of that object, which has to be extracted from images. The details of the object description are adjusted to a large start scale. Object parts, which are not observable at that scale, are also not represented in the object model. The automatic creation of the semantic net requires some constraints in order to be able to adapt the net to another scale. The second input of the process is the target scale, which has to be smaller than the start scale.

The first step is a decomposition of the semantic net. The goal of the decomposition is to identify parts of the semantic net, which can be processed separately. These parts can consist of single object parts or blocks of them, if the object parts influence each other during scale adaptation: E.g. two objects with a small distance to each other possibly have to be adapted together (depending on the target scale), because during the scaling process the small distance can disappear and the objects can merge.

The next step is the scale adaptation of the decomposed parts themselves. The selected object parts and blocks have to be generalized. In this process different aspects have to be taken into account: It is possible that the object type changes as well as the object attributes. All objects of the same object type exhibit a comparable behaviour in scale change and can be extracted by the same group of feature extraction operators.

For the scale adaptation of the elements scale change models are used. Scale change models describe the kind of change of a certain object type depending on the value of scale change. Different attributes, such as the grey value contrast of the object to the neighbours or the spatial measurements, are used as input parameters for the scale change models. Also analysis-by-synthesis methods were applied for the adaptation. The decision, of how to change the object parts or the blocks, has a direct connection to the question of how they can be extracted after scale change by using feature extraction operators. If it is necessary to change the feature extraction operators after scale change, the object type has changed. Hence, the scale behaviour of feature extraction operators has to be taken into account.

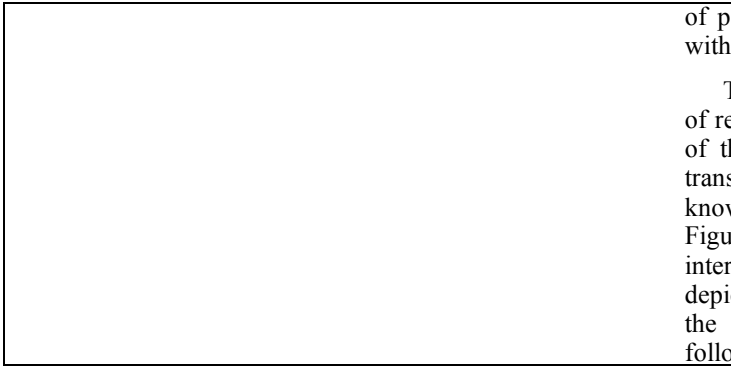


Figure 5. Strategy for Scale Adaptation

The last step is the fusion of the adapted object parts to a complete semantic net, which describes the object in the smaller scale and which can be used for an automatic object extraction in low resolution images.

Further information about the methodology and results can be found in [8] and [20]. The result of an automatic scale adaptation of the concept net in Figure 1. is depicted in Figure 6. The first object model is able to work in images with a resolution of 3cm/pel, the second one in images with 1m/pel.

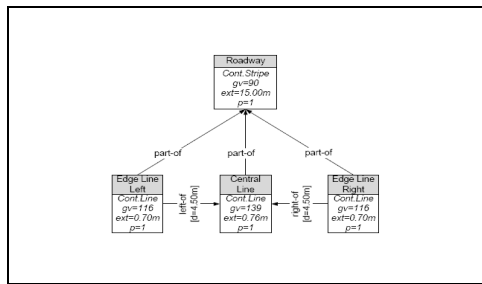


Figure 6. Concept Net after Scale Adaptation of Figure 1.

IV. MULTITEMPORAL INTERPRETATION

The object models described until know in this paper are suitable for the interpretation of one epoch. They are not able to handle multitemporal data. But for many applications it is of interest to do a monitoring. This is for example necessary for map updating or in order to recognise particular developments in special areas, which require reactions.

In literature different approaches for multitemporal interpretation of remote sensing data are discussed e.g. [15] [22] [31]. Some of them compare images of different epochs pixelwise, some of them compare them after separate multispectral classifications and some of them on the semantic level. The use of semantic information reduces strongly the search space of the multitemporal interpretation and thus improves the results. Different conditions for possible object changes from one epoch to another are formulated. Therefore, the objects in the scene are interpreted by using the knowledge

of possible temporal changes. The following approach works with this strategy.

The approach [21] discretely describes temporal conditions of regions, and it transfers the most probable temporal changes of the given conditions as temporal knowledge into a state transition diagram. Hence the temporal part of the prior knowledge is implemented into a state transition diagram. Figure 7. shows the state transition diagram for the interpretation of Moorland (the object model for Moorland was depicted in Figure 2.). During the multitemporal interpretation the state transition diagram is used to predict possible following classes in the next epoch, based on the prior interpretation. For further information see [21]. This kind of temporal modelling was also used in an approach for the monitoring of low resolution images in [17]. The result shows also in those images improvements compared with the results without using temporal knowledge.

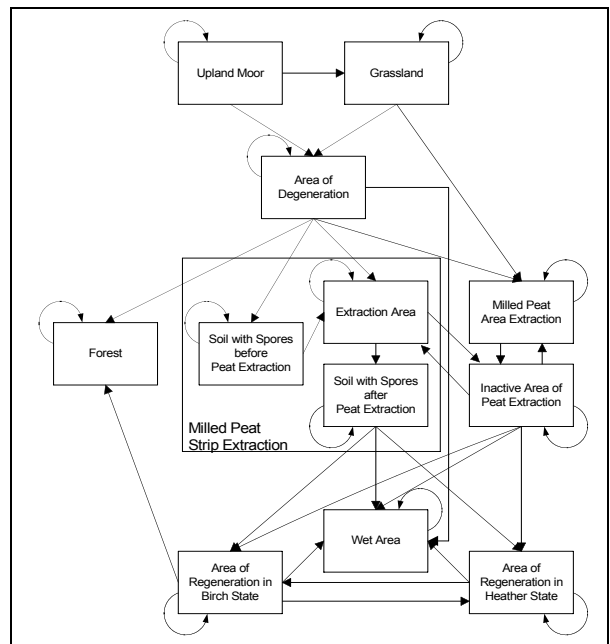


Figure 7. State Transition Diagram for Moorland

For the multitemporal interpretation of agricultural areas the developed concepts of state transition diagrams were extended by the development of continuous multitemporal models for the observable features (see Figure 8.). They contain the different feature values during the growing stages of crop fields. Therefore these models can be used to predict any growing stage of the crop fields. In order to be able to learn the continuous multitemporal models it is necessary to choose image sequences with a sufficiently high temporal resolution. So it is possible to interpolate between them to create a continuous sequence of the crop development stages.

The interpretation of crop fields is done by using observations in different epochs. For these epochs the existing feature values are computed. The goal is to assign the

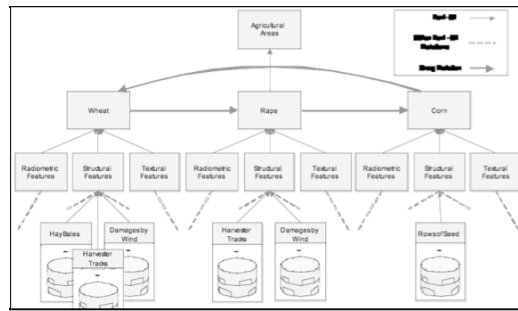


Figure 8. State Transition Diagram for Agricultural Areas

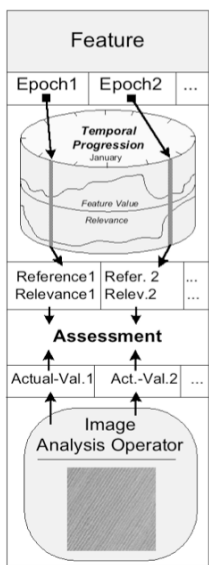


Figure 9. Comparison between Data and Model

computed feature values to one of the crop classes, which are represented by a set of multitemporal models.

The comparison between computed data and models is performed for every feature of a crop class separately. Figure 9. shows how the comparison is done. For every separate field to be interpreted all different features are computed for all observed epochs (\Rightarrow actual value). Then they have to be compared with the reference values of the crop classes. Because of possible temporal variations a search buffer around the observation epochs is created. By using also relevance values for every feature an assessment is done with an estimation how good the observed values for the different epochs fit to the multitemporal models. From the separate assessments an overall

assessment is computed which decides, how good the observed features fit to the crop classes. The field is assigned to the crop class with the best match.

In addition to the continuous multitemporal models also crop rotation will be used for the interpretation (see Figure 8.). Therefore the crop classes, which follow after each other from year to year, will be connected to each other in the semantic net. In this way the temporal history of a crop field can help to reduce the search space and to increase the interpretation accuracy.

V. CONCLUSIONS

In this paper several approaches for a structural interpretation of images for different applications were shown. All approaches were based on the use of object models represented by semantic nets. Furthermore a methodology for

an automated generation of object models was shown by an adaptation of existing object models to other scales. Finally a strategy for a refined multitemporal interpretation by using semantic information based on the above object representation was presented.

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