Knowledge Based Interpretation of Aerial Images and Maps Using a Digital Landscape Model as Partial Interpretation

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Abstract

The methods for the interpretation of aerial images and maps are usually different although both describe the same landscape. The presented work shows that regarding remote sensing data and maps as different kinds of sensors allows a similar approach for both in the domain of landscape interpretation. The prior knowledge about the landscape objects is represented explicitly by semantic nets. Based on the semantics of the network language a problem independent set of rules controls the scene interpretation.

Important is that the scene analysis employs a partial interpretation derived from a Digital Landscape Model (ATKIS DLM 25/1). This partial interpretation is used to generate an initial scene description. Consecutively the scene description is verified in aerial images and maps. Interpretation proceeds iteratively mixing top-down and bottom-up strategies.

This paper shows the representation of the knowledge in several semantic layers, the strategies of interpretation, and the methods to interprete aerial images and maps using a DLM as partial interpretation.

1 Introduction

The recognition of land use changes for map updating and environmental and agricultural monitoring represents a major topic of remote sensing. Long term changes of the environment can be obtained from the topographic map 1:25000 (TK 25) that is updated since about one hundred years. Due to the large amount of data photogrammetry and cartography work on the automatic extraction of objects from sensor data and maps. However, until now no prior knowledge about already mapped landscapes is utilized.

This paper presents an approach that integrates an existing partial interpretation derived from a GIS (ATKIS DLM 25/1) in the recognition process. The landscape is modelled in a semantic net, which contains the representation of the landscape in ATKIS and in different aerial images and maps. Moreover, the model contains query operations for ATKIS data and methods for extracting primitives from aerial images and maps.

In the first interpretation step an initial scene description is instantiated according to the ATKIS data. Consecutively the derived scene description is verified in aerial images and maps and adapted if necessary.

2 System Overview

Figure 1 shows the architecture of the knowledge based scene analysis system. The system is designed for the interpretation of aerial images and maps.

The prior knowledge about the objects to be extracted from the image data is represented explicitly in the knowledge base. Besides this general knowledge about the objects the interpretation takes advantage of a digital landscape model (ATKIS DLM 25/1) that contains the object location for some object classes. From the DLM a partial interpretation of the scene is derived. However the DLM has a limited accuracy and may be out-dated. Hence it has to be verified in the aerial images and maps that mirror the scene at the date of interest.

The interpretation module establishes an initial symbolic scene description based on the DLM which constitutes a hypothesis. This hypothesis is tested in the sensor data by

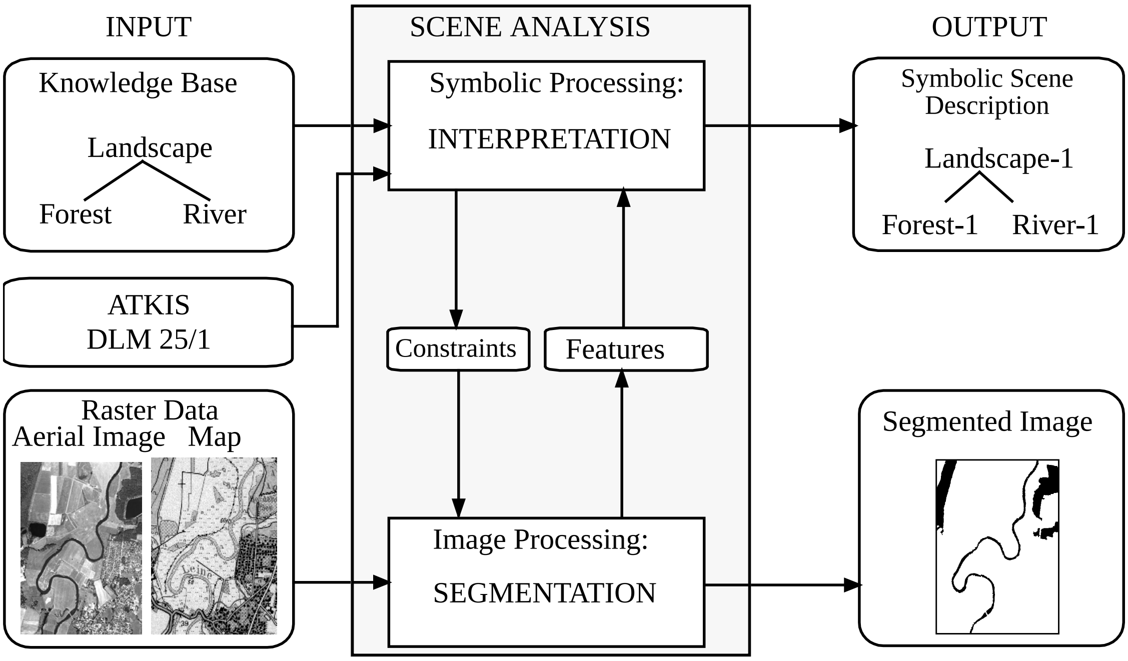


Fig. 1: Architecture of the knowledge based scene analysis system

generating constraints for the features expected in the image.

The image processing module extracts features that meet the constraints given by the interpretation module. It returns the found features and a reliability measure. The interpretation module groups the features and evaluates the relationship between the features to decrease or increase the reliability of competing interpretations. The interpretation results in a symbolic scene description and a corresponding segmented image.

3 A Language for Image Interpretation

3.1 Knowledge Representation

In the literature various systems for knowledge based scene analysis have been suggested. They employ different paradigms for knowledge representation like formal logic, fuzzy logic, frames (Clement et al., 1993; Foresti et al.; 1993), semantic nets (Niemann et al., 1990), and production systems (Matsuyama and Hwang, 1990; McKeown et al., 1985). Often knowledge about the objects and the control strategy is structured hierarchically (Foresti et al., 1993; Matsuyama and Hwang, 1990).

To cope with imprecision and uncertainty of sensor data the analysis systems has to combine bottom-up and top-down image analysis strategies, like SIGMA (Matsuyama and Hwang, 1990) and ERNEST (Niemann et al., 1990).

Usually the analysis results in many competing hypotheses. To reduce the search space analysis has to consider only the most promising hypotheses. To solve this indexing problem search methods are employed, like the A*-algorithm (Niemann et al., 1990) or production rules (Matsuyama and Hwang, 1990; McKeown et al., 1985) which exploit heuristics.

Most image analysis systems have been tested for selected examples, like the recognition of airports (McKeown et al., 1985), roads (Clement et al., 1993; Matsuyama and Hwang, 1990; Mayer and Steger, 1996), and buildings (Matsuyama and Hwang, 1990; Braun et al., 1995) in aerial images. A good overview about knowledge based scene analysis systems can be found in (Shapiro, 1992) and (Haralick and Shapiro, 1993). However, the data sets were small. Furthermore, image analysis should be able to take advantage of existing partial interpretations, i.e. GIS-data.

To ease the adaptation of the knowledge about the objects as well as the analysis strategy for new modelling tasks, the knowledge base has to be formulated explicitly.

Structural knowledge, like the knowledge about the relationships between the objects and their connection to the features apparent in the image data, can be represented efficiently by semantic nets. This kind of knowledge is termed fact knowledge. The procedural knowledge dictates how the fact knowledge will be used to control image interpretation.

Fact Knowledge is represented by semantic nets. Semantic nets consist of nodes and edges between them. Here, the nodes of the semantic net represent the objects in the scene or their sensor specific features respectively. The nodes are implemented as frames which contain a collection of attributes. Furthermore, an object has methods, i.e. functions, assigned to it to compute the attribute values. Additionally, an object can possess a method to segment the object in the image data.

Here the syntax of the semantic net distinguishes between two types of nodes: concepts and instances. The concepts describe the generic model of the objects. The instances are realizations of the concept in the observed scene. During interpretation four different states of the object recognition are distinguished: hypotheses I_H, missing instances I_M, partial instances I_P and complete instances I_C. Hypotheses are not yet verified in the sensor data. Falsification in the sensor data results in missing instances, while verification obtains partial and complete instances successively. Complete instances possess all obligatory parts of the object. Partial instances describe a predecessor state that contains already all obligatory parts that are not context dependent.

Interpretation starts with hypotheses instances which are initialized with the attributes of the concept. Methods assigned to the object attributes restrict the expected range of attributes top-down and obtain the measured value bottom-up from the sensor. To model uncertainties the attributes are described by minimum and maximum values and ranges. The differences between the expected range and the measured value is judged by a compatibility measure.

The nodes are related by different types of edges or links. The instances are related via *instance-of* to their concepts.

The specialization of an object is described by the *is-a* link. This link type introduces the concept of inheritance.

Objects are composed of parts, indicated by the *part-of* link. Object search can be reduced to a more simple task, the detection of its components. Furthermore some parts may only be detectable if other parts have already been detected and thus established a certain context. These context dependent parts are modelled by *cdpart-of*.

Objects can often be detected based on their geometric or photometric appearance, that can directly be segmented in the image data. This transformation of an abstract symbol to a concrete realization is represented by the concrete-of link, abbreviated *con-of*. The *con-of* link allows to distinguish between different conceptual layers, e.g. geometry and sensor.

The *data-of* link establishes a relation to the features segmented in the image data. A present *data-of* link indicates that the object can be segmented directly in the sensor data by image processing operators.

Geometric or photometric relations between objects can be represented explicitly by *attributed relations*. This link type contains an attribute that restricts the attribute value of the related object. While the *is-a*, *part-of*, and *con-of* relations propagate information top-down or bottom-up the *attributed relation* propagates information mainly horizontally.

Counters in the links of the concept net state how many links are required, i.e. obligatory, and allowed, i.e. optional, in the instance net.

Procedural Knowledge states how and in which order scene analysis has to proceed. A strategy is represented by a set of problem independent rules. These rules exploit only the semantics of the network language. The advantage of this approach is that the rules are independent from the domain knowledge. According to the number of link types only a small set of rules is required.

A rule is composed of a condition and an action part. The condition checks for a new interpretation state of neighboured nodes in the semantic net. The action part adapts the interpretation state of the focused node accordingly. The knowledge, for example, that an object n_0 is detected and can be denoted as complete instance I_C, if all its parts $n_i \in P$ are detected, is represented by following rule:

<u>Rule-complete-instantiation:</u>

CONDITION: If state (node n_i) = complete instance

$\forall n_i \in P$ $P = \{n_i | n_i = \text{part-of}(n_0)\}$

ACTION: Then state(node n_0) = complete instance.

The sequence of the instantiation process is controlled by the priority of the rules. Rules which verify a node as partial or complete instance or falsify as missing instance have a higher priority than rules which generate new hypotheses. To favour top-down control the rules for top-down propagation of hypotheses are tested before bottom-up hypothesis propagation. Furthermore obligatory parts are searched for first followed by context dependent and optional parts. Attributed relations constrain the search space. Hence the associated rules have a high priority.

The rule based formulation of the control strategy eases the development and testing of new control strategies.

3.2 Control of Interpretation

The aim of image interpretation is to assign a symbolic description, i.e. semantics, to the data. Image interpretation exploits the generic model to instantiate hypotheses of objects expected in the scene. Interpretation is complete when an instance of the goal concept is found based on the generic model net and the features, which are segmented in the image data.

Figure 2 shows the interpretation process. The interpretation exploits the knowledge base to derive a symbolic scene description from the input data. Each possible interpretation is documented by a search node which contains all concepts and instances with their current interpretation state. If competing interpretations occur the search node splits into child search nodes. The leaves of the resulting search tree represent the currently competing interpretations. To focus interpretation on promising search nodes they are judged and ranked. The judgement computes the compatibility between expected properties and

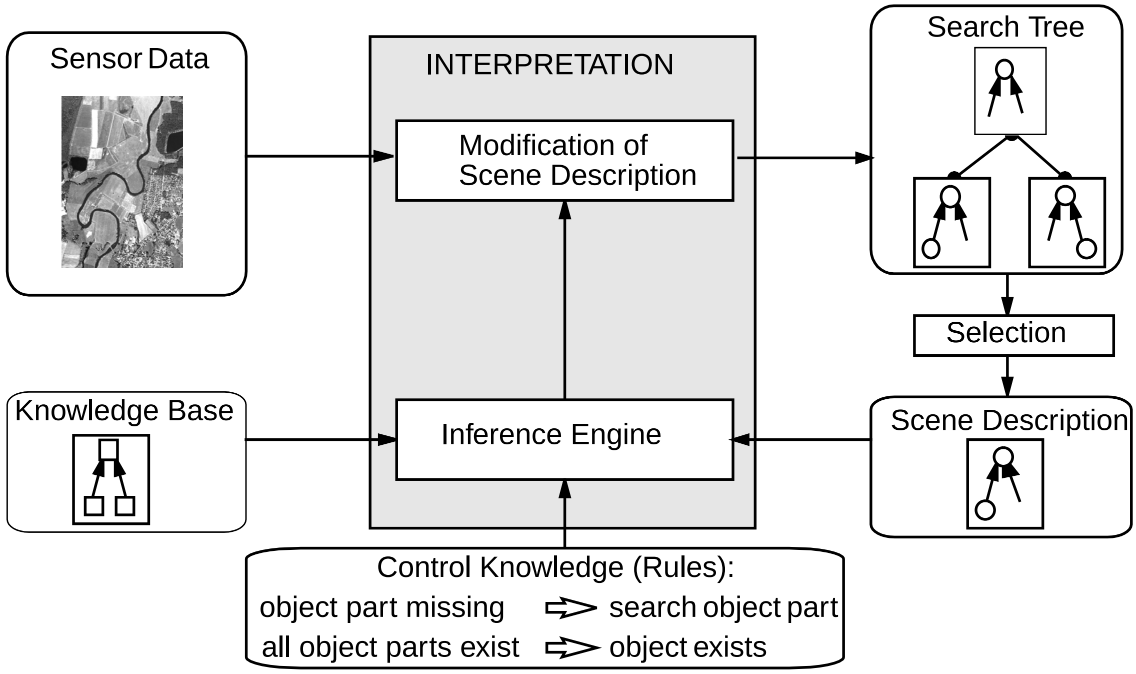


Fig. 2: Interpretation process

found properties of the scene description. An A*-algorithm selects the interpretation judged best for further investigation.

The instance net of the selected scene description is compared with the concept net in the knowledge base. The condition part of the rules takes care of the comparison. Interpretation employs an inference engine which controls the execution of the rules. According to the set of rules and their priority different strategies are possible. Usually the comparison matches for the condition of more than one rule. To select one rule the rules are ranked. The rank of a rule depends primarily on the priority of the rule in the selected strategy and secondly on the rank of the node for which the rule matches. The rank of the node corresponds to the distance of the node to the bottom data nodes, measured in the number of required hops via the links. Here, to favour immediate verification in the sensor data the nodes are ranked bottom-up.

The selected rule is executed and modifies the scene description by establishing new links or changing the status of a node. Competing modifications of the scene description cause the current search node to split for each possible interpretation. Competing interpretations occur if

- a segmentation method returns more than one feature that meets the request,
- a node is specialized, or
- a node establishes links to other nodes that are exclusive.

Here, to avoid an explosion of the search tree, hypotheses are primarily propagated top-down from the scene layer to the sensor layer to verify them in the sensor data. At the sensor layer the propagated hypothesis calls methods for segmentation. The result of the verification is returned to the superior instance which consecutively generates new hypotheses.

3.3 Implementation

The described approach is implemented as a knowledge based interpretation system called AIDA. The control algorithms of the system are implemented in C++ with a Tcl/Tk interpreter interface. A graphical user interface provides browser and editor functionality for monitoring and knowledge acquisition.

4 Using GIS Data as Partial Interpretation

4.1 ATKIS

The partial interpretation is derived from the 'Authoritative Topographic Cartographic Information System (ATKIS)' (Grünreich, 1992), which has been developed by the German state Ordnance Surveys. ATKIS data is available in most states of the Federal Republic of Germany. Here the Digital Landscape Model (ATKIS DLM 25/1) is used, which contains objects that correspond to the contents of the TK25.

In ATKIS the surface of the earth is divided into objects that are represented as points, lines and areas. The definition of the objects is described in a hierarchically structured feature catalogue. On top of the hierarchy the objects are divided into domains of object classes, e.g. hydrography, transportation, and vegetation. These domains are distinguished by groups, e.g. road traffic, and rail traffic, which are finally divided into object classes, e.g. road, and path. Each object is assigned to exactly one object class. A more detailed description of the objects is realized by attributes. For instance, an object of the object class road possesses the attribute motorway or federal road.

Depending on the topographic structure an object is divided into one or more parts. Attributes can be assigned to the whole object or to its parts. The geometric information (point, line or chain, area) is attached to the object parts. Topological relationships like the connection between nodes and edges of the road net are not stored explicitly, but the rules for building objects and object parts ensure that they can be obtained by identical nodes, e.g. crossroads, or lines, e.g. confluence of rivers which are stored as areas. Another spatial relationship the overpass/underpass reference is attached explicitly to an object part that is above or below another object part.

4.2 Integrating ATKIS Data

The ATKIS data is stored in the GIS Software Sicad/open. A simple query language has been developed to enable query operations on the ATKIS data. Possible queries are: selection of objects by their properties within a search area, description of attributes of a selected object, description of the geometry of a selected object. It is also possible to query spatial relationships of an object, e.g. topological connections.

The query language is implemented in Tcl/Tk. Hence it can easily be integrated into AIDA.

4.3 Representing ATKIS Data in a Semantic Net

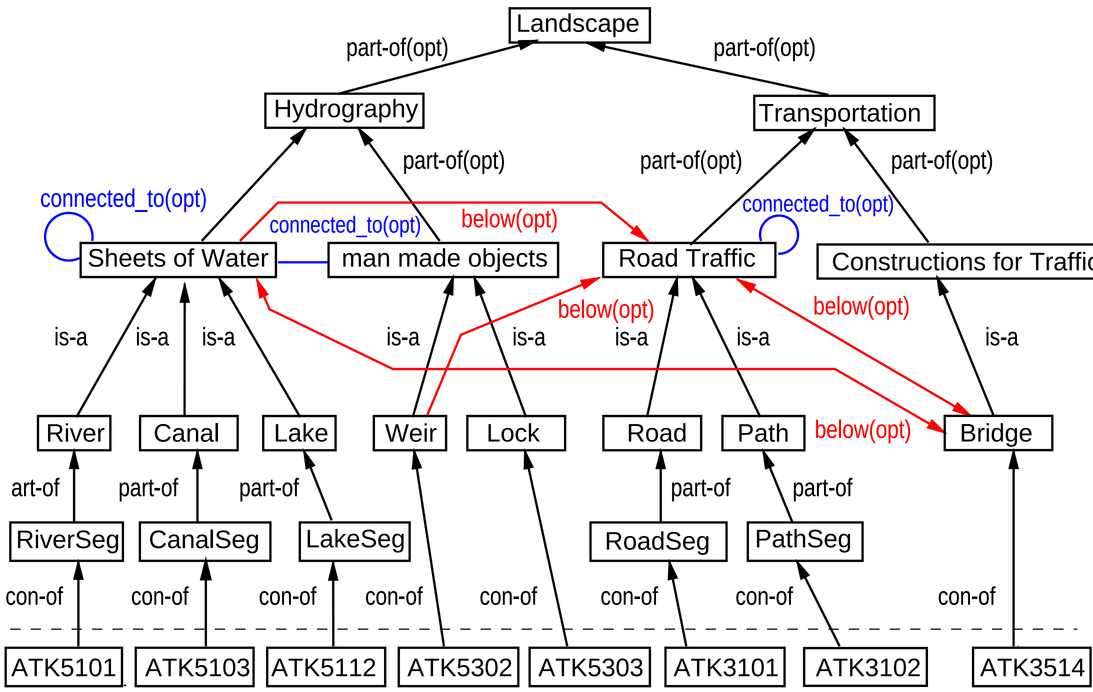


Fig. 3: Representation of ATKIS in a semantic net

Figure 3 shows a part of the semantic net representing ATKIS. In this part the *landscape* is divided into *hydrography* and *transportation*. Because both of them are not obligatory parts of the described scene, they are represented as optional parts of the landscape. *Hydrography* consist of the optional parts *Sheets of Water* and *man made objects*. *Sheets of Water* are specialized as *River*, *Canal* and *Lake*. This is represented by the *is-a* relationship. Each of this objects consists of at least one segment. These segments have a concrete realization as ATKIS objects. The transition from the abstract scene description to the concrete realization is represented by the *con-of* link. The number of the objects, e.g. ATK5101, correspond to the code of the object classes in ATKIS. The objects *Weir*, *Lock* and *Bridge* are not divided into segments because they have a direct representation in ATKIS.

In addition to the hierarchical relationships *attributed relations* are attached to the objects to model spatial relationships. For example a topological connection of objects is represented by the *connected-to* link. Objects that are on top or underneath another are connected by the *above* or *below* relationship.

5 Interpretation of Aerial Images

During the last years several methods for the analysis and interpretation of aerial images and other remote sensing data have been suggested.

A standard method is the analysis by classification (Mueller, 1992; Dennert Moeller, 1983). The limits of the classification method depend on the used data and are examined in (Michaelis, 1989). The use of different sensors by sensor fusion made a further improvement of the analysis. A good overview is given by Mueller (1989).

An interpretation of aerial images by knowledge-based object recognition was realized by Xu (1993) and led to a higher amount of recognized objects. All these methods contribute to the presented approach.

In the following the used method for the interpretation of aerial images is described which employs semantic nets and exploits an ATKIS database. As mentioned above the objects from the ATKIS DLM are used as a partial interpretation. Because the used DLM may be out-dated and has a limited accuracy, at first a verification of the ATKIS DLM with the used aerial images is necessary.

Hence the verification of the used ATKIS data is both the basis for the interpretation and the first application. The used domains of object classes are vegetation and hydrography. In the following this verification is described. The description is devided into two parts: The generation of an ATKIS scene description and its verification.

5.1 Generation of an ATKIS Based Scene Description

An ATKIS based scene description has to be generated for those areas of the aerial images which have to be examined. To do this the examined objects are taken from the ATKIS database and represented as instances in the semantic net, which is the basis of the following interpretation. One of the examined object classes is forest.

To generate a scene description a generic model, i.e. a concept net, is needed. The concept net consists of concept nodes and contains the considered objects in all needed levels of abstraction with all required relations between them. An instance net is built by instantiation of the concept net. This instance net is the realization of the concept net for the considered scene and contains the scene description, at first the ATKIS based scene description.

The used concept net is structurally a simplification of the net that describes the ATKIS database. Only the objects to be examined are included. The described spatial relations will be considered later and are not included yet. Figure 4 shows on the left side the concept net for the generation of an ATKIS based scene description for forest-objects. Two levels of abstraction are distinguished, the scene layer and the ATKIS layer.

Instantiation. To show how an instantiation process proceeds in the following the instantiation of the concept net in figure 4 is described. It starts with a seed node in the instance net. According to the strategy and its priority of rules the instantiation proceeds in a particular order along the relations postulated in the concept net, until no more rules can be applied and the instance net is complete.

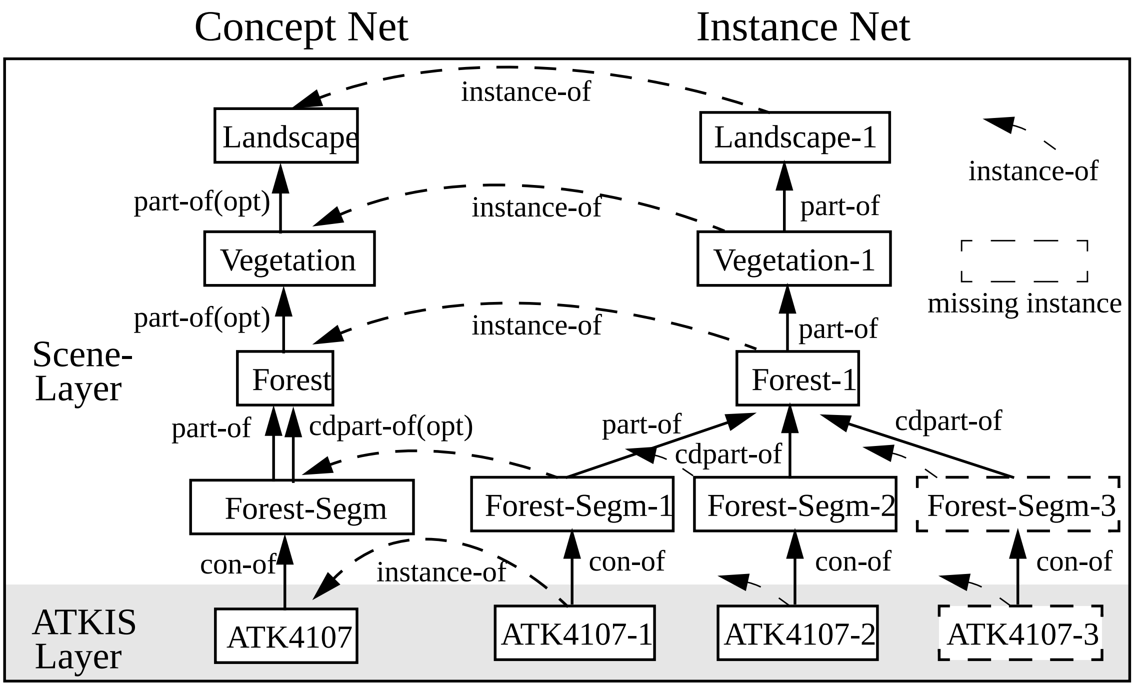


Fig. 4: Instantiation of a concept net

Here, to start the instantiation process a hypothesis I_H(*Forest*) is instantiated. That means a new node with the status hypothesis is created (*Forest-1* in fig. 4) and connected by an *instance-of* relation to the concept node C(*Forest)* in the concept net. The condition of the rule for complete instantiation (see 3.1) is not fulfilled because the obligatory parts are not present. Hence the rule for top-down propagation of a hypothesis is executed. This leads to an instantiation of the concept node C(*Forest-Segm*) along the *part-of* relation. The node *Forest-Segm-1* with the status hypothesis is created. In the same way *ATK4107* (4107 is the code of forest-objects in ATKIS) is instantiated as the hypothesis *ATK4107-1*. Now the bottom layer is reached. The concept node *ATK4107* at this layer, named ATKIS layer, contains a method that selects an ATKIS object 4107 through the ATKIS interface (see 4.2), which is inside the analysed area. If the method returns an ATKIS object the hypothesis becomes a complete instance. That means the instance node *ATK4107-1* changes its status from hypothesis to complete instance. Now all obligatory context independent parts of *Forest-Segm-1* are present. Hence this node becomes a partial instance.

The status partial instance blocks the bottom-up propagation till all obligatory and optional context dependent parts of *Forest-1* are detected. In this way all *Forest-Segm* of the *Forest*-1 are selected consecutively from the ATKIS database and are instantiated in the semantic net.

When all *Forest-Segm* of the *Forest* are extracted, the method returns no further object from the ATKIS database. Hence *ATK4107-3* becomes a missing instance instead of a complete instance. Consecutively *Forest-Segm-3* also becomes a missing instance. This is the condition to stop the creation of new *Forest-Segm* hypothesis via *cdpart-of(opt)*.

Finally the node *Forest-1* becomes a complete instance, because all obligatory parts are present.

Because no more top-down rules can be executed now the nodes *Vegetation* and *Landscape* are completely instantiated bottom-up. After this the net is completely instantiated.

In contrast to the obligatory parts the instantiation of optional parts can be performed as often as desired or not all. This has important consequences. The absence of a forest in the scene resulting in a missing instance of *Forest-1* does not lead to a missing instance of the node *Vegetation-1*.

ATKIS Attributes. In the instance net each forest possesses at least one *Forest-Segm* and one *ATK4107* node. The position and the form of the ATKIS objects are stored as attributes in data nodes. The data nodes are connected via *data-of* relations to the *ATK4107* nodes. This data nodes also contain other ATKIS attributes, which can be used in the later interpretation. For example, each forest object contains the ATKIS attribute vegetation feature. The vegetation feature contains the information whether a forest segment belongs to the group coniferous forest, deciduous forest or mixed forest. The stored attributes can be propagated from node to node.

5.2 Verification of the ATKIS based scene description

Now all needed ATKIS objects are instantiated in the semantic net. To continue with the verification in the aerial image, an aerial image layer has to be added to the concept net. As shown in figure 5 the aerial image layer is connected like the other sensor layers through a geometry layer to the scene layer. The addition of the new layers requires to reset the status of the nodes in the scene layer to hypothesis instance to avoid contradiction in the semantic net.

The verification in the aerial image uses the generated ATKIS based scene description as a hypothesis. Since the position and the form of each object is known from ATKIS, the

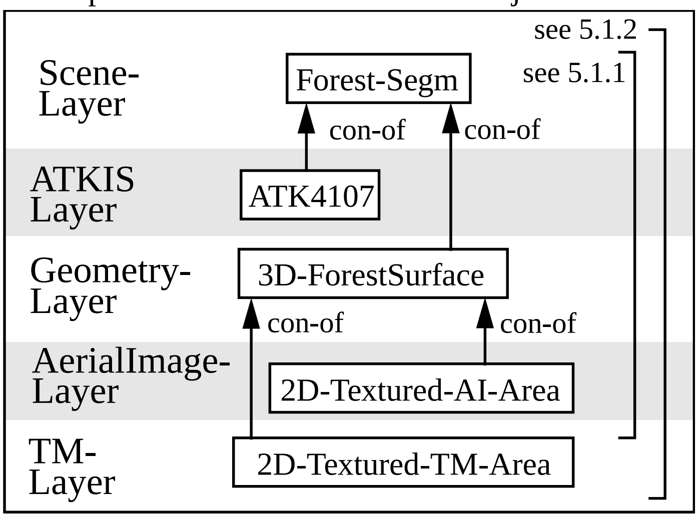


Fig. 5: Connection of sensor layers

hypothesis is propagated top-down to the aerial image where the corresponding object is expected in the same position with the same form as in ATKIS.

The verification of the semantic net in the aerial images leads to the instantiation of the hypothesis *3D-ForestSurface* and *2D-Textured-AI-Area*. This has to be verified in the aerial image. For this the node *2D-Textured-AI-Area* contains an image processing operator, which is executed after the instantiation of the hypothesis. In the following this operator is described

Verification in the Aerial Image. In the verification process the operator uses the prior knowledge of ATKIS, that there is an object of a particular type. The geographic coordinates of the objects are included in the instance nodes of the ATKIS layer as attributes. In the sensor layer the coordinates are converted into the aerial image coordinates. Exactly the area, which is obtained from ATKIS, is the area to be examined in the aerial image and is termed verification area in the following. The assumption of the verification in aerial images is, that the major part of the verification area is homogenous regarding particular texture parameters. Hence the texture parameter values for the searched objects show up as a maximum in the histogram of the texture parameters inside verification area. The searched objects can be extracted easily.

Problems occur if the assumption above is not fulfilled and the searched object does not fill the major part of the verification area. This happens if, for example, a forest area has been cleared and replaced by a housing estate or a field. In that case the texture parameter values of the searched object would result into a local maximum and the extraction of the object with the absolute maximum would lead to a falsification.

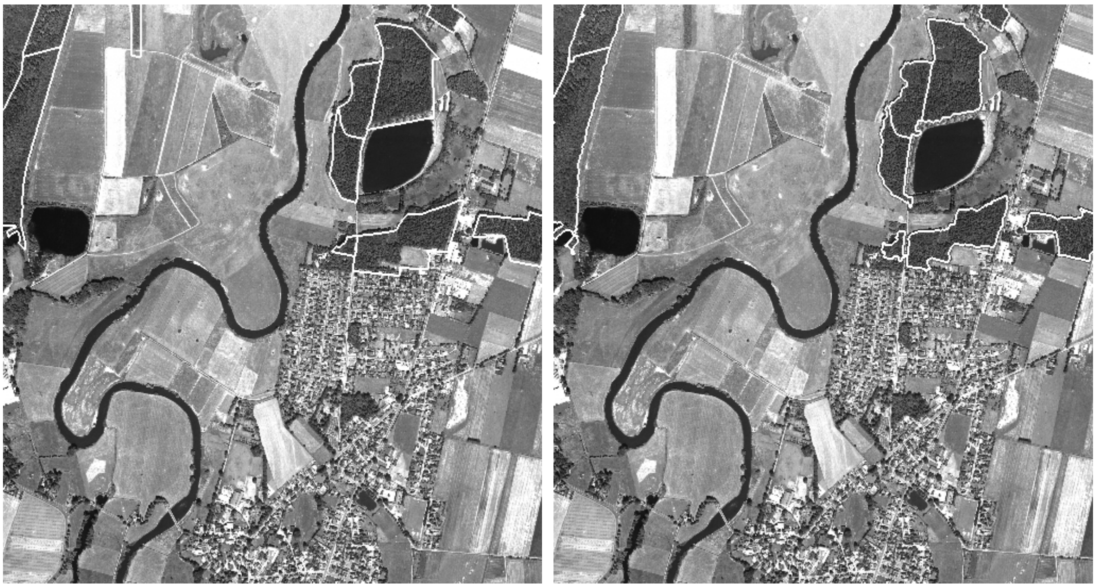
Hence at first a learning phase is executed. In this phase the most frequent texture parameters inside the verification area are determined, even if some of them belong to other object classes. The texture parameters, determined by the image processing operator, are returned to the corresponding nodes and saved as attributes.

These determined texture parameters are now propagated bottom-up from node to node until they merge in the node *Forest-1* (see fig. 4). In this node reference parameters are estimated from all parts. The texture parameters describe either the searched object or a complete different object. Because of this some of the determined texture parameters are close together and some of them are far away from each other. Hence the estimation of the reference parameters has to be robust (Press and Flanery, 1989).

The estimated reference parameters establish the prior knowledge how the scene objects are represented in the aerial image sensor. These reference parameters are now propagated top-down. In the aerial image layer the image processing operator exploits the additional knowledge about the texture and is now capable of extracting the correct object, even if the object fills only the minor part of the verification area.

The actually used verification area is a little bit larger than the area indicated by ATKIS in order to detect also a small expansion.

The described method of aerial image verification assumes that the differences between the examined objects in the aerial image data and the ATKIS data are not too large.



ATKIS Data   Verified Data

Fig. 6: Result of verification

Otherwise the determined texture parameters would be to inaccurate causing false reference parameters.

On the other hand this kind of verification works without further prior knowledge about the object texture in the aerial images. This knowledge is acquired during the verification.

The advantage of this verification is the independence from contrast and brightness of the used aerial images. The aerial images could even be replaced by images of other sensors.

Verification Result. The result of the described verification of ATKIS data for the object class forest is shown in figure 6. The used texture parameters are the local variance and the local contrast in an area of $400m^2$. The left picture shows the objects taken from ATKIS before the verification. The right picture depicts the verified data. Inside the verification area all boundaries are adapted very good. One segment with texture features different from the other is not identified as forest.

5.3 Sensor Fusion

After the verification the actual position and form of the ATKIS objects are known. To improve the interpretation further and to make it more robust, more information can be taken from other sensor data, if available. The new sensors have to be included in the concept net, like the Landsat/TM-sensor in figure 5. The texture parameters for each verified forest segment are computed from the TM bands and stored as attributes.

Consecutively the interpretation uses this additional knowledge to improve the verification of objects.

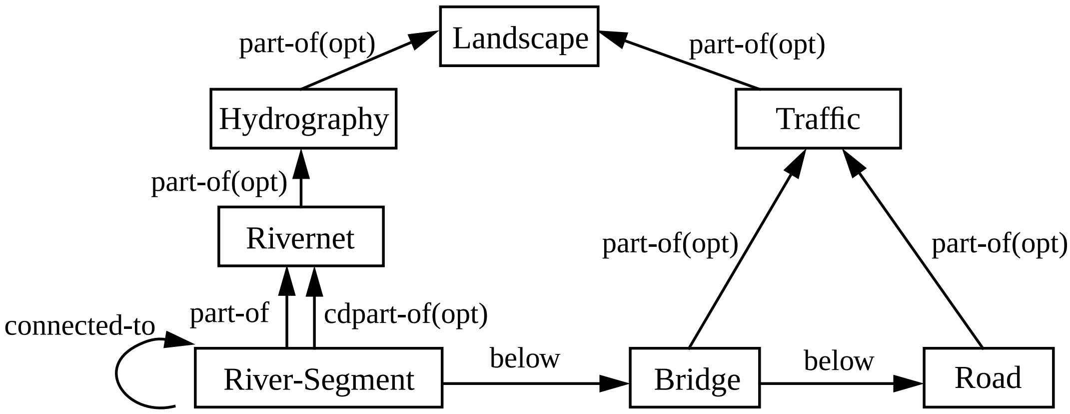


Fig. 7: Concept net with spatial relations

5.4 Spatial Reasoning

The use of spatial relations will improve the interpretation because additional knowledge is used. In the following an approach to find bridges above rivers is presented.

Figure 7 shows a concept net with spatial relations. The spatial relations are realized as *attributed relations*.

The prior knowledge that the river net and also the road net are contiguous is modelled by the *attributed relation connected-to*. That means each *River-Segment* is connected to another. Furthermore the prior knowledge, that a *River* runs only below a *Bridge* and that a *Bridge* only runs below a *Road*, is modelled by the *attributed relation below*.

During interpretation all *River-Segments* are checked for a break. In that case the hypothesis is instantiated that there is a *Bridge* above the *River*. After that the hypothesis for a *Road* above the *Bridge* is instantiated. To verify this hypothesis the aerial image is analysed in the interrupted area regarding texture and grey values. The result of this analysis leads to a verification or falsification of the *Road* hypothesis inside the break. After verification the *Bridge* becomes a complete instance.

To continue the interpretation from this point it is possible to find the contiguous road net by tracking the roads beginning with the found bridge.

6 Interpretation of Maps

The maps to be interpreted are taken from the German official map series 1:25000 (TK25). This map series was produced for the first time about one hundred years ago for the former German Reich. Therefore it is an important source for the detection of long term land use changes.

As data origin digital raster data of colour separated layers is used. The data is vectorized and attributes like line width and layer are attached. The vector data is then stored in a GIS. The interpretation process uses these pre-segmented primitives as basis data.

6.1 A Model of the Map Graphics

Figure 8 shows a part of the map graphic represented in a semantic net. The scene layer corresponds to that introduced in section 4.3. The *con-of* links of the *CanalSeg* represent the transition from the scene layer to the realization of a canal segment in ATKIS and in the map. The concept *CanalSegMap* represents the canal segment in the map layer. The depiction of a canal in the TK25 map depends on its width. For that reason a canal is specialized in a canal with a width less than three meters, which is depicted as a single blue line and a canal that is wider than 3 meters. This specialization is represented by the *is-a* relationship. A wide canal consists of two *banks* and the *canal bed*. In the map the bed is depicted as a blue area which is represented by a *con-of* link to the concept *blue area* in the graphics layer. The bank symbol can either be a *wall* or a normal *bank line* that is depicted as a *black line* or a *blue line*.

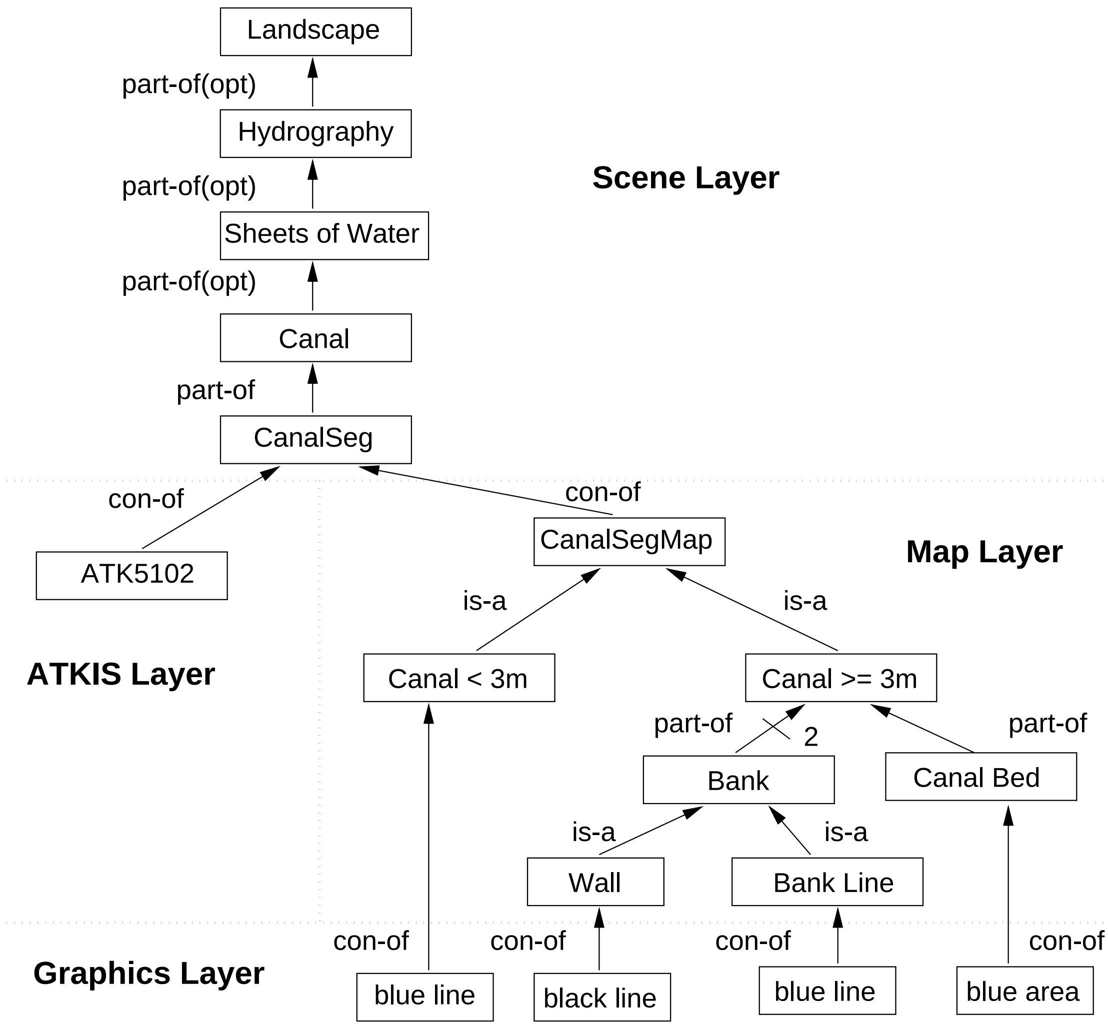


Fig. 8: Model of the map graphics

6.2 Instantiation

The essential process of interpreting the map corresponds to that described in section 5.1 and 5.2. At first the concept nodes of the scene layer are instantiated using the ATKIS data. After that they are verified in the map data using the instantiated scene description as a hypothesis. The hypothesis, e.g. of a canal segment, is propagated top-down. The relevant information obtained from ATKIS is also propagated top-down in the corresponding attributes of the nodes. Getting to the graphics layer the methods of the nodes *blue line*, *blue area* etc. are used to select corresponding map primitives. Here, the method is a GIS operation that creates a buffer around the reference geometry derived from ATKIS and searches within this buffer for primitives with the postulated attributes. The selected primitives are rated by a distance function. For each selected primitive an instance is created and the primitive is marked as used. According to the search strategy rules for creating partial and complete instances are then applied until the search goal is reached.

7 Conclusion

The basic aim of this project is the interpretation of remote sensing data and maps. The applied approach is based on one hand on the use of the ATKIS database (DLM 25/1), which can be accessed during interpretation. Furthermore, the knowledge based approach eases the extension to new object classes and other sensors.

To realize this the knowledge based interpretation system AIDA was developed, which provides a language for image interpretation based on semantic nets. The semantics of the network are exploited by a problem independent set of rules to control interpretation.

Furthermore, an interface was developed in order to connect the ATKIS database fully automatically to AIDA. This connection enables access to any ATKIS object and to any spatial relation.

The system was tested for the extraction of the ATKIS object classes forest and river from aerial images and maps. Analysis proceeds in two steps. At first a symbolic scene description is established from the ATKIS database. In the second step the ATKIS based scene description is verified in aerial images and maps. The scene description is adapted to the current data and object changes are detected.

The first results show that the presented approach is suitable to solve the examined problems and provides a huge potential to improve the interpretation.

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