# KNOWLEDGE BASED INTERPRETATION OF OBJECTS IN TOPOGRAPHIC MAPS AND MOORLANDS IN AERIAL IMAGES


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Semantische Modellierung; *SMATI 99*

**KEY WORDS:** Knowledge Based System, Semantic Net, Agent System, Adaptive Image Processing, Learning, Moorland Interpretation, Map Analysis, GIS, Multitemporal Interpretation, Monitoring



## ABSTRACT

For the automatic interpretation of remote sensing data and maps prior knowledge derived from a GIS and general knowledge about the properties of the scene objects, such as form, size and texture, can be used to preset constraints for the interpretation process. The image primitives to be interpreted are extracted by image processing algorithms which need in most cases a number of parameters. Due to varying image quality, accuracy etc. these parameters have to be adapted iteratively to the data to get appropriate results. This paper presents a knowledge based interpretation system which uses semantic nets for knowledge representation and an adaptive image processing system based on agents. The agent system adapts the parameters of the segmentation algorithms automatically and learns, which algorithm is suitable for the current data and the given task and which initial parameter values are reasonable. Two examples demonstrate the applicability of the system for different tasks, the interpretation of moorland in aerial images and the extraction of roads from topographic maps.


## 1 INTRODUCTION

The automatic interpretation of remote sensing data and maps represents a major topic of Photogrammetry and Cartography. In Photogrammetry the automatic interpretation is needed for the identification of objects and areas in remote sensing data in order to observe certain areas or to create or update topographic and user specific maps. One application is the observation of environmentally sensitive regions, such as moorland. The usual approach for such problems were data driven multispectral classification methods up to now. But classification approaches work only for a limited number of object classes. Such object classes have to be homogenous regarding colour or texture. Further the results of data driven image processing algorithms are often erroneous for example due to noise, and varying illumination or because object boundaries do not coincide with the luminance contours in the image. In order to solve that problems and also to interpret more complex object classes additional knowledge has to be used. Additional knowledge about Moorland can be the knowledge which results from certain conditions that people must observe, if they work on those areas. These conditions make sure that the moor area will be protected. Some areas may only be cultivated during fixed periods, which are determined by administrative authorities. Further knowledge can be the knowledge about the structures, which can be found in moor areas like tracks or vegetation.

In Cartography the automatic interpretation is needed for different tasks. One is to analyse topographic maps in order to obtain information for the automatic generation of maps from a digital landscape model. Further the interpretation of the topographic map TK25 could be used for an integration of user specific data into the DLM25, because the user specific data is usually based on the TK25. After creating the connection between the DLM25 and TK25 by analysing the map, the connection can be reversed for the integration of user specific data. A third application is the recognition of long term land use changes by interpreting old maps, created at different epochs. The additional knowledge used for these tasks can be the knowledge about the structure and colour of signatures and their relations in maps.

A modern system for image analysis has to use additional knowledge about the scene objects in general and/or specific knowledge about the observation area like the data of a geoinformation system (GIS). The interpretation results can be further improved by exploiting the data from different acquisition epochs. The required flexibility for the automatic interpretation can be achieved using a knowledge based approach which separates the knowledge from the control of the scene analysis. By exchanging the knowledge base the system can be adapted easily to varying application tasks. The knowledge is used to formulate constraints for the object extraction process and for the interpretation of the image features.

For the interpretation of aerial images and maps we use the knowledge based image interpretation system AIDA. It generates a symbolic scene description by assigning semantic meanings to extracted image primitives. Similar to the system ERNEST [Nie90] it formulates prior knowledge about the scene objects by means of semantic nets. In addition the control knowledge is represented explicitly by rules. The system integrates data from a GIS and combines information from multitemporal images.

For the segmentation of the image data an adaptive image processing system is used. According to a task description given by the semantic net the system selects a suitable segmentation algorithm. The parameters are adapted automatically until the segmentation results coincide with the task description as well as possible. Finally the optimal results are returned to the interpretation system.

In the following sections we describe the knowledge based image interpretation system AIDA (section 2) and the adaptive image processing module (section 3) based on agents. In section 4 we treat the use of these systems for the interpretation and monitoring of moorland, in section 5 for the interpretation of topographic maps.

## 2 KNOWLEDGE BASED INTERPRETATION SYSTEM

For the automatic interpretation of remote sensing images the knowledge based system AIDA [Liedtke et. al. 1997] has been developed. The system strictly separates the control of the image analysis process from the semantics of the scene.

### 2.1 Knowledge Representation

The knowledge representation is based on semantic nets. Semantic nets are directed acyclic graphs and they consist of nodes and edges in between. The nodes represent the objects expected in the scene while the edges or links of the semantic net form the relations between these objects. Attributes define the properties of nodes and edges.

#### 2.1.1 Nodes

The nodes of the semantic net model the objects like frames [Minsky, 1975] of the scene and their representation in the image. Two classes of nodes are distinguished: the concepts are generic models of the object and the instances are realizations of their corresponding concepts in the observed scene. Thus, the knowledge base which is defined prior to the image analysis is built out of concepts.

During interpretation a symbolic scene description is generated consisting of instances. An instance is a member of a search node wich is a consistent (particular) interpretation of the image and can have the following states:

- *hypothetical instance:* the first vacant instance of a concept in the search node.
- *partial instance:* not all obligatory parts and concrete nodes are complete.
- *complete instance:* all attributes are set and all obligatory parts and concrete nodes are complete.
- *missing instance:* falsification of an instance.

The object properties are described by attributes attached to the nodes. They contain an attribute value which is measured bottom-up in the data and a range which represents the expected attribute value. Attribute values are transformed e.g. from world units like meters to image units like pixels. Expectations about object properties are translated into a task description for the adaptive image processing module which is described in section 3. The semantic net uses the segmented image primitives and assigns a semantic meaning to them.

### 2.1.2 Relations

The relations between the objects are described by edges or links forming the semantic net (Fig. 1). The specialization of objects is described by the *is-a* relation introducing the concept of inheritance. Along the *is-a* link all attributes, edges and functions are inherited to the more special node which can be overwritten locally. 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. It is possible to differenciate between optional and obligatory parts. The transformation of an abstract description into its more concrete representation in the data is modeled by the concrete-of relation, abbreviated *con-of*. For example a road in the scene layer is presented as stripe in the image layer.

Image processing algorithms supply objects and properties about them. To integrate this information the *data-of* link is realisied. Attributed relationen such as neighborhood can be formulated by the *att-rel* link. For example a street is represented in an image as a lot of stripes which only have small distances between a couple of stripes.

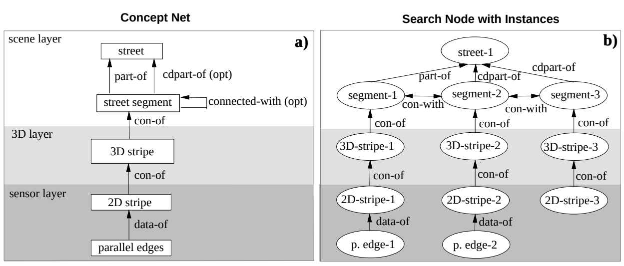


Figure 1: Semantic net for road detection (part)

This relation allows to structure the knowledge in different conceptual layers like for example a scene layer and an image layer. Based on this knowledge representation scheme a common concept has been developed to distinguish between the semantics of objects and their visual appearance in different sensors. In Fig. 1a you can see the knowledge base which is represent as a net of concepts. The symbolic scene description for an image is examplary shown in Fig. 1b which show a search node and the contain instances. Furthermore domain specific knowledge like GIS data can easily be integrated to support and strengthen the interpretation process. An example of a semantic net for the interpretation of moorland is described in section 4.

## 2.2 Control of the Scene Analysis

To make use of the knowledge represented in the semantic net control knowledge is required that states how and in which order scene analysis has to proceed. In principle two approaches of analysis strategy are possible:

- *Bottom-up:* group and interpret the results from the image analysis.
- *Top-down:* try to find the objects which are expected from the knowledge base in the data.

During the analysis this two strategies are alternating. On the other hand it must be possible to handle alternative interpretations.

### 2.2.1 Rules

The control knowledge is represented explicitly by a set of rules. Each rule ist composed of a condition and an action part. The condition checks for each instance the actual state of this instance and the neighboured nodes. The rule for instantiation for example changes the state of an instance from hypothesis to complete instance, if all subnodes which are defined as obligatory in the concept net have been instantiated completely. If an obligatory subnode could not be detected, the parent node becomes a missing instance. An inference engine determines the sequence of rule execution.

### 2.2.2 Judgement

Whenever ambiguous interpretations occur they are treated as competing alternatives and stored in the leaf nodes of a search tree. The best judged interpretation is selected for further investigation. Using a mixed top-down and bottom-up strategy the system generates model-driven hypotheses for scene objects and verifies them consecutively in the data.

The range of each instance attribute is predefined and/or calculated during the interpretation. For each attribute a value and range computation function has to be defined. A judgement function computes the compatibility of expected range and measured value.

To choose the best search node from the search tree for the next step an A* Algorithm is used. In the next we explain how to calculate the assessment for the A* Algorithm from the actual attribut values and the expected interval for this value. In this case we must deal with uncertainty and imprecision data. For example:

- A proposition like the node *street* is uncertain if it can not be classified clearly.
- The value of the attribute road width is imprecise if it possesses no accurate value.

The possibility theory [Dubois, 1988] allow to handle uncertainty and imprecision.

**Modelling of Uncertainty** The Dempster-Shafer [Shafer 1976] theory devided for each proposition $e$ the interval $[0..1]$ into three intervals (Fig. 2). These three intervalls necessity $N(e)$, necessity of the contrary proposition $N(\neg e)$ and the ignorance $\Theta$ describe the uncertainty of a proposition. If no knowledge about the proposition $e$ exist $N(e)$ and $N(\neg e)$ are zero. The possbility $P(e)$ is given by:

$$P(e) = 1 - N(\neg e)$$

During the analysis each measurement decrease the ignorance.

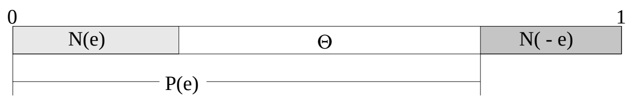


Figure 2: Necessity $N(e)$ and Possbility $P(e)$

**Modelling of Imprecision** Imprecision can be modeled with fuzzy sets [Zadeh, 1979] which describe the membership of a value $x$ to the hypothesis $H$ with a function in the interval $[0..1]$ (Fig. 3). A certain membershipvalue $a$ is interpreted as possibility $p(a)$ that a proposition $x$ *possesses the value* $a$ is true for the assumption $x$ *is* $H$.

The combination rule that is defined for fuzzy sets allow to calculate with imprecise attributes. For an imprecise hypothesis $H$ and a given imprecise measurement $E$ the possibility and necessity is given by:

$$P(H|E) = \sup_{x \in X} \min(P_H(x), P_E(x))$$

$$N(H|E) = \inf_{x \in X} \max(P_H(x), 1 - P_E(x))$$

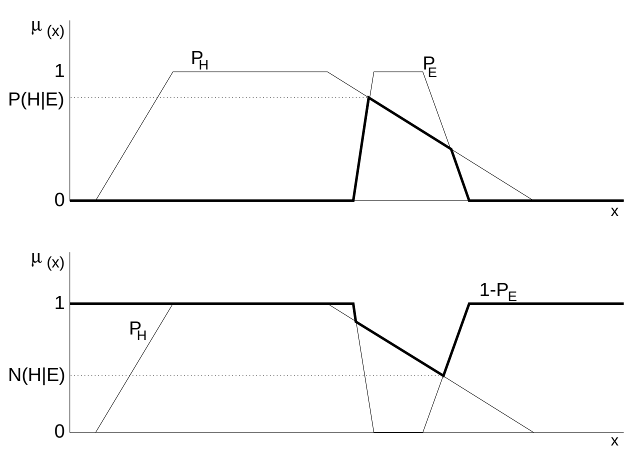


Figure 3: Computation of possibility $P$ and necessity $N$ of a hypothesis $H$ for a given evidence $E$

**Combination of Information** The judgement of all instances of one search node supplies the valuation for it and the judgement of one instance results from its actual attribute values. To combinate this several values two different cases can be note. The first is that the values have a complementary character and second the character is complete. The necessity $N(e)$ and the possibility $P(e)$ for complementary values $i$ are given by:

$$N(e) = \min_i N(e_i)$$

$$P(e) = \min_i P(e_i)$$

The corresponding approach to compute the joint necessity $N(e)$ of redundant sensors from the maximum of the cues fails if the sensor information is in conflict, i.e. one suggests $e$ and the other $\neg e$. In this case $N(e) + N(\neg e) \leq 1$ is not guaranteed. To consider contrary information the cues of redundant sensors are combined similar to Dempster's rule of combination. All combinations of sensor information that support the proposition $e$ are summed up (black rectangles in Fig. 4). The sum is normalized by the sum in the denominator of all combinations that are not contradictory (all but white rectangles in Fig. 4). The combination is associative and commutative. Hence it can be written for two sensors without loss of generality.

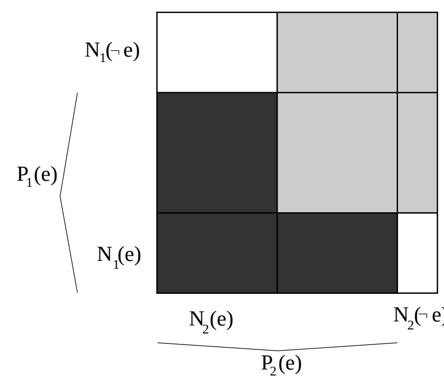


Figure 4: Combination of compet values

$$N(e) = \frac{N_1(e)P_2(e) + N_2(e)P_1(e) - N_1(e)N_2(e)}{1 - N_1(e)N_2(\neg e) - N_1(\neg e)N_2(e)}$$

$$P(e) = 1 - N(\neg e)$$

### 2.3 Extension to Multitemporal Images

Applications like change detection and monitoring require the analysis of images from different acquisition epochs. By comparing the current image with the latest interpretation derived from the preceding image land use changes and new constructions can be detected. Prerequisite for this is the possibility to save scene descriptions in form of instantiated semantic nets and to load and reuse them as expectation for the next image. To increase the reliability of the interpretation the knowledge about possible state transitions between two time steps should be exploited. For the representation of these state transition diagrams in the semantic net the different states are modelled by concept nodes. They are connected by a new relation: the temporal relation. It is used to model the possible or most probable state transitions within a time step. For each temporal relation a priority can be defined in order to sort the possible successor states by decreasing probability. As states can either be stable or transient, the corresponding state transitions differ in their transition time which can be also specified in the temporal relation.

During scene analysis the state transition diagram is used to generate hypotheses for the next observation epoch. For each of these possible state transitions a hypothesis is generated. All hypotheses are treated as competing alternatives represented in separate leaf nodes of the search tree. Interpretation continues using the next image in the chronological order. An example for the exploitation of a state transition diagram is outlined in section 4.

## 3 AGENT SYSTEM FOR ADAPTIVE IMAGE PROCESSING

The term agent is known from the AI (Artificial Intelligence) and describes autonomous working units [Newell, Simon 1972]. Agent technology is one of the fastest growing areas of research and new application development. Agents are used in almost all applications that claim some intelligent functionality or will perform tasks automatically. Jeffrey [Jeffrey, 1997] offers a classification of agents based on the following characteristics.

1. The functionality of the individual agent e.g.:
   - a simple sensor / actor system like a function
   - a function that can distinguish different situations
   - autonomic systems with flexible behavior
   - learning and reflexive agents
   - collective working and collaborative agents
2. The communication among the agents.
   - communication only between two agents
   - communication via a blackboard
   - variable communication between the agents
3. The location of the agents
   - the whole system runs only on one computer
   - a distributed system on different computers/operating systems
   - mobile agents that can change their location

In our application the task of the agent system is the automatic parameter adaptation for remote sensing data interpretation. The semantic net or an user supplies a task description formulating the goals for the image processing operator and information about the images used. The goals refer to the features of the image processing results e.g. the features of the segmented areas. Necessary information about the image are for example resolution and sensor model.

Another requirement of the agent system is its learning ability. The system should learn which image processing operators are suitable for which tasks. Further the favorable start parameters for the image operators should be learned to speed up the adaptation process.

In the following, the design of the agent system and the parameter adaptation for the image operators is presented, focussing on the information required for adaptation and its connection. As operators we use the tools from the Khoros [Khoros, 1997] system.

### 3.1 Design of the Agent System

The agent system is implemented as a distributed system with learning and reflexive agents under CORBA (Common Object Request Broker Architecture). CORBA is the specification of the interfaces and architecture of the ORB (Object Request Broker) by the OMG (Object Management Group).

One agent, the main or client agent represents the interface to the semantic net or an user and communicates with the other agents, called server agents. Each server agent contains an image processing operator and an adaptation unit for this operator.

The structure of the agent system design is depicted in Fig. 5. The ORB manages the communication between the agents and provides basic services like name service and trading service.

### 3.2 Adaptation

Each server agent contains one image processing operator which usually has a number of parameters. With different parameter settings different results are returned from the operator. The goal of the adaptation is to find the parameter set that provides the best result. To determine the best result the features of the

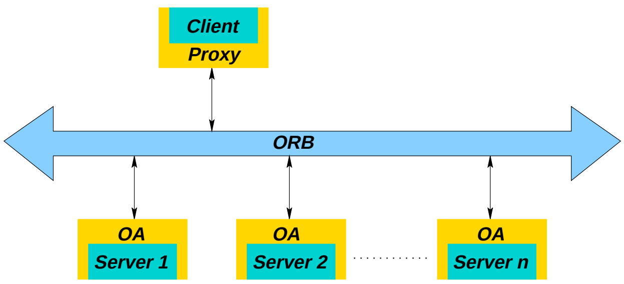


Figure 5: Agent system design

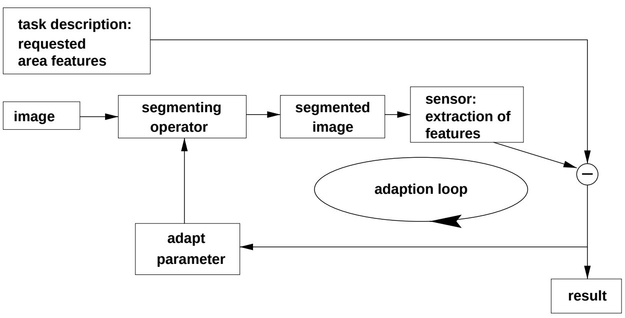


Figure 6: Parameter adaption

segmented image are calculated and compared with the task description.

The adaptation of the parameters for the image processing is based on the iteration shown in Fig. 6. The image processing operator is applied to the input image with the predefined start parameters. Then the resulting image is compared with the given task description according to the features of the areas found. The parameters are adapted by a set of rules and the calculation is repeated. For each operator the rules must be supplied by the user. This iteration continues until the optimal result has been found [Rost, Münkel 1998].

### 3.3 Parameter Adaptation

The set of possible goals consists of given values for the attributes of the extracted regions. These are:

| | |
|---|---|
| area size | area count |
| compactness | convexness |
| ratio of holes | texture |
| roundness | rectangularity |
| length | radial ratio |

These measures are modeled according to [Rosenfeld, 1976] and [Abmayr, 1994] and they are normalized to the range of [0..1]. The goal value of one attribute can also be given as a range. The importance of an attribute is set by means of the interval width. A predefined attribute range of [0..1] indicates for example that the value of this attribute is irrelevant for the given task. The narrower the range, the more important the attribute is.

### 3.4 Attribute Range

To describe a segmentation result either the attributes of all segments are averaged or only the best segment for the adaptation is used (Fig. 7). In this way for example the following tasks can be formulated:

1. Find a round object whose area size should be within a default range.
2. Find areas as rectangular as possible (man made) and larger than a minimum size.

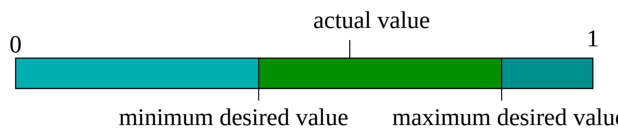


Figure 7: Attribute range design

### 3.5 Cooperation

Cooperation means to process a task in common [Albayrak, 1993]. This cooperation is implemented as a contract negotiation in which the client agent negotiates with potential server agents, the so-called contract-net procedure [Davis, 1988]. Three steps of negotiation are distinguished in the presented agent system:

1. The advertisement of a global task. In this step, the agents unsuitable for the task are excluded from the following negotiations.
2. The remaining agents receive information about the data and the goals of the operation to estimate their suitability to solve the task.
3. In the last step, one or more agents are instructed to process the task.

### 3.6 Learning

The basis of the learning procedure is the above mentioned set of negotiation functions between the agents. The aim of the learning procedure is to organize the behavior of the agents in such a way that the task given to the agency can be processed as well and as specifically as possible.

Learning within the agent system requires two steps to be carried out, the selection of a suitable image processing operator and a reasonable initialization of the parameters to be adapted. In order to accomplish these tasks the described procedure of the contract net is extended in two aspects:

1. The acquisition of credit values in accordance to the quality of an agent to solve the specific tasks.
2. Selection and activation of agents as contractors according to their credit values.

Consequently the result of learning is a more specific selection of the contractors but also a faster adaptation of the parameters for the image processing by use of a data base. The agents learn for which tasks they are suitable and how to solve known problems. An agent learns its task specifically by using a credit vector.

For the automatic acquisition of these credit values, the results supplied from an agent are matched with the required goals. This comparison describes the ability of the agent for the current task and is stored in the credit vector. The credit vector consists of the following four entries:

1. order count: the number of tasks for the agent and/or an agency.
2. work count: the number of tasks, that are processed by the agent and/or an agency.
3. success count: the number of tasks which are processed successfully by the agent or an agency.
4. confidence: this value represents a kind of self appraisal of the agent and/or of the agency in solving the current task. This value consists of the current setting of a task (sensor type and ground resolution) and the previously mentioned credit values.

If the server agent has already processed tasks with different goals, it selects the credit vector which is most similar compared to the current task. To choose this vector the ratio of the agreement and the difference to the current task is computed. For initialization the stored parameters from the most similar task are used as start parameters.

## 4 INTERPRETATION OF MOORLAND IN AERIAL IMAGES

This section describes the use of the knowledge based interpretation system in order to do a moor interpretation. In section 4.1 we will describe briefly the prior knowledge we used for interpretation of moorland, and in section 4.2 the further input data. The conversion of prior knowledge into our knowledge based system as semantic nets and the interpretation procedure itself will be shown in 4.3, the results in section 4.4. The concept to extend the system into a multitemporal interpretation and further results will be described in section 4.6.

### 4.1 Prior Knowledge

Originally, moors were upland moors. In Germany these have practically vanished. Today mostly grassland, forest and area of regeneration or degeneration are found in the former upland moors.

In most cases parts of moorland are used for peat extraction. Degeneration is the state before peat extraction takes place. For this purpose the ground must be drained by means of ditches. Then peat extraction is possible. Usually harvester machines are used. In aerial images the use of the machines can be recognized by tracks. After peat works have finished, a regeneration of the moorlands will begin. In most cases people will simply stop working on the land and leave it to regenerate, which eventually will result in increasing vegetation. Hence in this state of land use vegetation can be found on these areas as well as tracks from the harvester machines from the state before. Some areas in moors have a higher level of protection. In such areas peat extraction is not allowed. Works in this areas are only allowed if they have the goal of regeneration. [Göttlich, 1990]

### 4.2 Input Data

Our test area is the moor area near Steinhude in Lower Saxony. We work with aerial images with a resolution of 0.5m/pel. The main input sources are CIR-images, but we also tested the results with grayscale images. The reason is that although colour images have more usable information, most recorded aerial images are grayscale images.

The second input source is a label image. In this step we presume to have the segment borders. This follows from the fact that a biotope mapping is performed at least one time for every moor area in Germany by ground survey. This is also prior knowledge we use in our system. For this we use a label image based on a biotope mapping. The label image masks the different segments of the aerial image, which is to be interpreted.

### 4.3 Interpretation with Semantic Nets

We use the knowledge based system with the explicit representation of prior knowledge, as described in section 2, to interpret the regions in the moor area. Therefore, the prior knowledge about the relevant area is formulated in a concept net. Fig. 8 shows a simplified version of the concept net.

We determined four states of land use for moorland: *forest*, *grassland*, *area of de-/regeneration* and *area of peat working*. The states *area of degeneration* and *area of regeneration* are combined, because their distinction in aerial images is very difficult. As shown

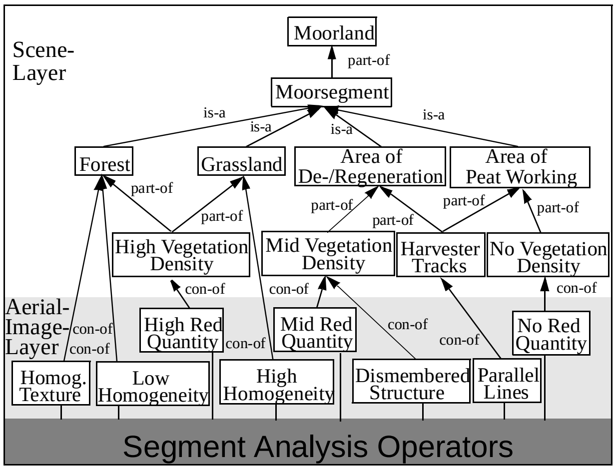


Figure 8: Concept net for the interpretation of moorland

in Fig. 8 we distinguish two layers of abstraction in the concept net: a *scene layer* and an *aerial image layer*. In the *scene layer* the different states are described with their obligatory parts. E.g. the state *area of peat working* has on the one hand *harvester tracks*, on the other hand *no vegetation density*. The state *area of de-/regeneration* has also *harvester tracks* in one part, but the second part is *mid vegetation density*. The nodes in the second layer, the *aerial image layer*, describe the depiction of the scene layer nodes, the land use states, in aerial images and their properties. The nodes describe the structures and colours to be looked for, if a state is to be assigned to a segment. At the bottom of Fig. 8 *segment analysis operators* are shown. Every node at the bottom of the *aerial image layer* has access to a special operator. The task of the respective operator is to verify the meaning of the node for a particular segment.

The interpretation process is called instantiation. To show the instantiation process in our case, it is described in the following. It starts with a start 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.

Here the instantiation process starts with the creation of a hypothesis of the concept *moorsegment*. At this point one segment is taken from the label image. The interpretation for this segment will now be performed. As shown in Fig. 8 there are four different possibilities of interpretation (states) for the segment. These possibilities exclude each other and therefore compete with each other. The first state to be verified is *area of peat working*: A concept node *area of peat working* will be created. Two obligatory parts of this node have to be present: *harvester tracks* and *no vegetation density*. This leads to the top-down instantiation of the concept *harvester tracks* along the *part-of* relation. The concretisation of *harvester tracks* is *parallel lines*, which also leads top-down to a creation of a hypothesis *parallel lines*. Now the bottom layer is reached and this hypothesis has to be verified. The node calls a special *segment analysis operator*. The operator examines the aerial image within the given segment and returns whether parallel lines were found or not. If the result is positive the operator returns a certainty to the node, which describes the quality of the result, and then the instance node *parallel lines* changes its status from *hypothesis* to *complete instance*. This leads bottom-up to a complete instantiation of the node *harvester tracks*. In the same way the second obligatory part of the node *area of peat working* will be verified and for the second verification also a certainty will be determined. Now all obligatory parts of *area of peat working* are present and the node is instantiated completely. Also a certainty for this node will be computed from the nodes below. The result is a possible interpretation of the moorsegment with a certainty value. If the certainty is not good enough the other competitive interpretations have to be verified in the same way.

### 4.4 Result of Moorland Interpretation

In Fig. 10 the result of the interpretation based on the label image of the biotope mapping and on the CIR aerial image of the test area (Fig. 9) is shown. The result of the interpretation reveals, that all 33 segments were interpreted as a human operator would interpret them using only the aerial image without stereo and ground truth information.

Figure 9: Aerial image of the used test area

A second interesting result of the interpretation is achieved, if we use a grayscale aerial image instead of a CIR aerial image. For this purpose all upper nodes in the aerial image layer of the concept net in Fig. 8 were removed. Hence the interpretation is only supported by texture information. 5 of the 33 segments could not be interpreted and 4 differed from the result shown in Fig. 10. The misinterpreted segments were mostly small, narrow or not typical for the land use states. This result shows, that colour information brings in fact additional information, but for most unproblematic regions texture information is sufficient.


Figure 10: Interpretation result of the test area

### 4.5 Moorland Segmentation

The assumption, that for every moorland a biotope mapping exists is true for Germany, but not for every country. In that case an initial segmentation is necessary. For this task it is also possible to use the *adaptive image processing system* described in section 3.

For the adaptation an image processing operator based on the *split and merge* procedure has been used. In addition the course of the roads is included in the segmentation. The adaptation goals were the same for all the image segments. The result of the adaptation is depicted in Fig. 11.

### 4.6 Multitemporal Image Analysis

The goal of multitemporal image analysis is the monitoring of moorlands. We have to extend the system described so far by multitemporal strategies. The multitemporal interpretation begins with an initial interpretation for the aerial images taken at the first epoch t to be interpreted. Then the next epochs t+n have to be interpreted in cyclical intervals based on the results of the interpretation before. These results restrict the search space and lead to an improvement of monitoring.

Fig. 12 shows an overview of the structure of the system concept. Beginning with the part *knowledge based interpretation* an initial interpretation of the

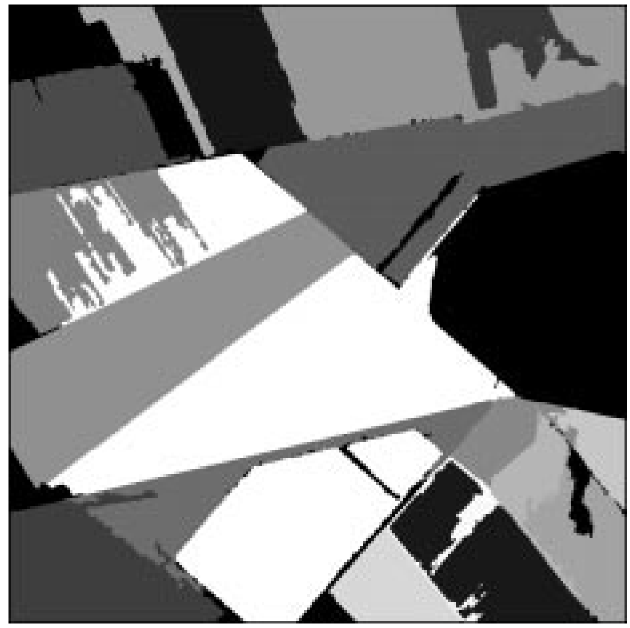

Figure 11: Segmentation result using the adaptation with Split and Merge

segments is performed. The results are *interpreted segments* of moorland. These segments are the input for a *prediction of state transitions*.

This prediction uses prior information concerning the possible changes. The possibilities are represented in a *state transition diagram*. A description follows below. The output of the prediction are *predicted new states* for every segment.

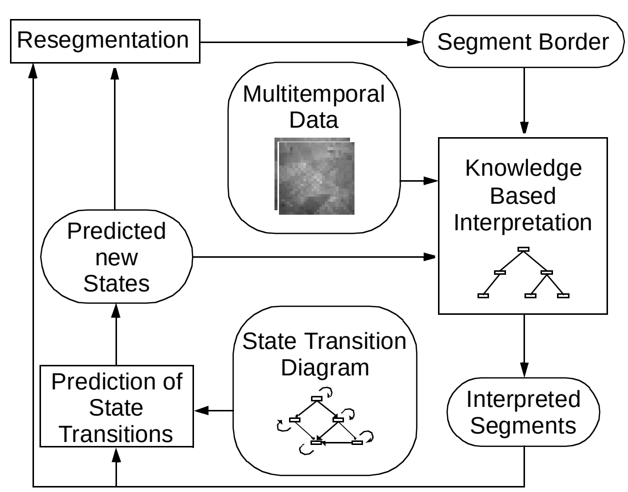


Figure 12: Concept net for multitemporal moorland interpretation

The borders of the segments may change between the interpretation intervals. Therefore, for the multitemporal approach we include a module to examine segment splitting by segmentation. The approach of the *adaptive image processing module* is described in section 3. This approach use the information of the *predicted new states*. The results of this step are updated segment borders, which are integrated into the *knowledge based interpretation* for the new epoch, just like the predicted new states and the multitemporal data.

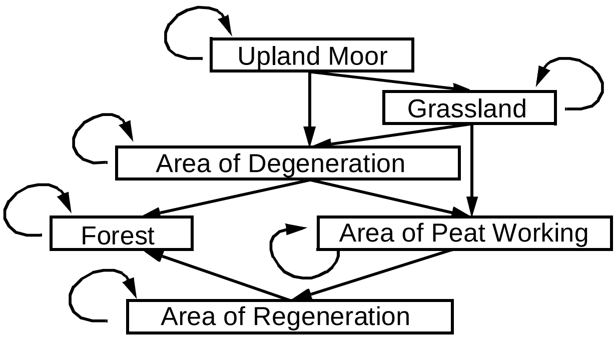


Figure 13: State transition diagram for changes in moorland

The *state transition diagram* in Fig. 13 describes the most probable state transitions. Although many more state transitions are possible there are restrictions by law and nature (see section 4.1). This enables us to use the restrictions in order to improve the interpretation. The presented *state transition diagram* applies only for the areas with a lower protection level. A diagram for the areas with a higher protection level would not have the state *area of peat working* because this is not allowed.

In contrast to the concept net in Fig. 8 this diagram contains six different states. The first state, *upland moor*, is implemented only to complete the diagram. Because *upland moor* does not exist anymore in the test area it will not be used in the interpretation. The states *area of degeneration* and *area of regeneration* are now separated. As mentioned in section 4.3 their distinction in aerial images taken at one epoch only is very difficult. But in a multitemporal interpretation with the prior knowledge described in the diagram the development of the different segments can be used also. For example given an *area of peat working* the system will know, that this segment has passed the state *area of degeneration*, and if in a new epoch an operator will find for example vegetation, the only states can be *area of regeneration* or *forest*. Every link in the *state transition diagram* has a priority, which describes the probability of the state transitions. This value affects the order in which the different state transition hypotheses will be verified. As shown in Fig. 13 every state has a transition link back to itself. This is in each case the link with the highest probability. Consequently for every new epoch this is the first transition concept to be verified.

In Fig. 15 a result of the usage of the *state transition diagram* is shown for two grayscale aerial images taken at two epochs. For the first epoch the aerial image were divided into three segments. For every segment the system determined the state transition.

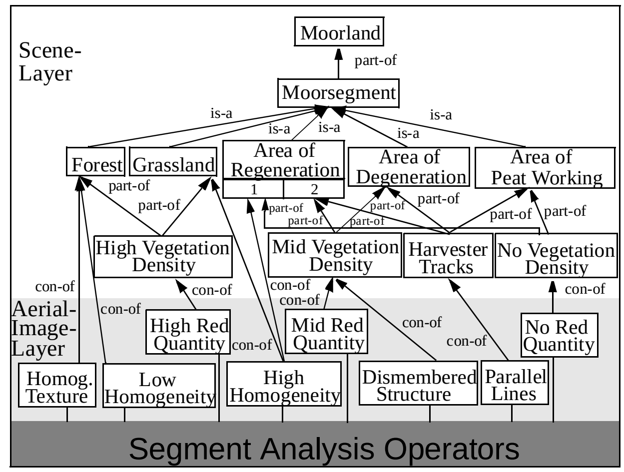


Figure 14: Extended concept net for multitemporal interpretation

The semantic net we used for the multitemporal interpretation is a refinement of Fig. 8 and is depicted in Fig. 14. In addition to the separation of the states *area of regeneration* and *area of degeneration* the state *area of degeneration* has also the description *high homogeneity*, because this is also a possible appearance of this state.

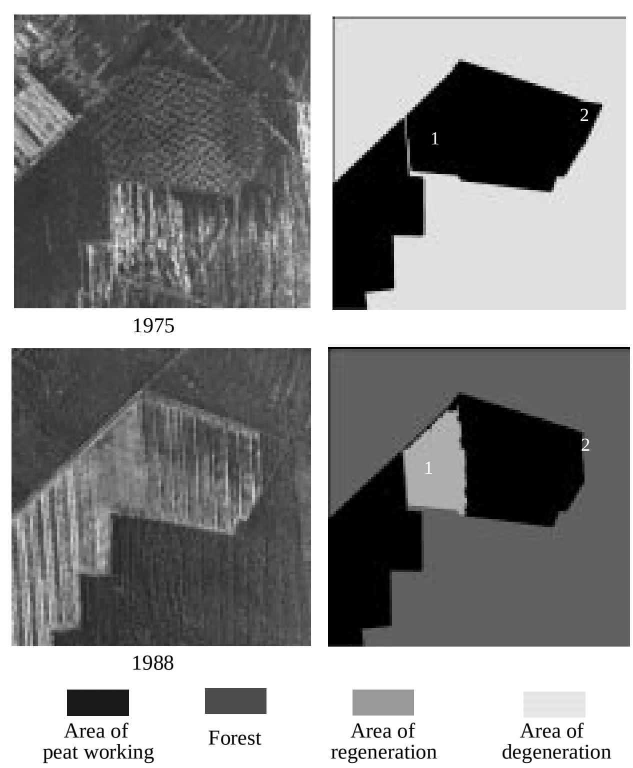


Figure 15: Usage of state transition diagram for multitemporal interpretation

The lower image on the right side of Fig. 15 is the result of the resegmentation. The resegmentation was carried out for every segment of the upper right image in Fig. 15 seperately by the agent system as described above in the overview of the whole system. The optimization was applied for the parameters *convexness, rectangularity* and *area size*.

The reduction of the search space for the possible successor states leads to a correct interpretation of the segments. For segment 1 a transition from *area of peat working* to *area of regeneration* is stated using the knowledge about the previous land use of the segment. Without using this prior information the system could not distinguish the states *grassland* and *area of regeneration* in grayscale images because both states are also characterized by a *high homogeneity*. For segment 2 the land use state changed from *area of peat working* to *forest* although there is no direct state transition between them represented in the *state transition diagram*. Due to the elapsed time of 13 years the state *area of regeneration* was not observed. But using the knowledge about the mean transition times the system also generated the hypothesis for *forest* which was verified successfully for segment 2.

In section 2 the tools for creating multitemporal interpretations in semantic nets were described. In the following the realization for the present case using these tools will be shown. We described above the overview of the system concept in Fig. 12. For the interpretation we have to implement the part for *state prediction* and the *state transition diagram* into the semantic net, described in section 4.3.

The semantic net used for this purpose takes advantage of temporal links in addition to the other one shown in Fig. 14. These links will be included for the interpretation of the next epoch (t+1) after the complete interpretation of the initial epoch t. During the interpretation of every segment with a particular state several hypotheses will be created along the temporal links. These hypotheses exclude each other. According to the priorities the verification of the different *state transition hypotheses* will be processed in a particular order. The search tree splits (see section 2.2). In case of a good result of a verification, the other competitive hypotheses will not be verified anymore. At the end of the instantiation for t+1 all instance nodes of the interpretation for the time t will be removed, and the interpretation will continue for t+2 in the same way.

## 5 INTERPRETATION OF TOPOGRAPHIC MAPS

The interpretation takes advantage of data from a geoinformation system (ATKIS) which is used as a priori knowledge for the further analysis of the scene.

For the knowledge based interpretation of the map, a model of the landscape is created that represents the different shaping of objects in the ATKIS data model and in the map.

In the first step a scene description is derived from the GIS data. This initial scene description is then used as a priori knowledge for the interpretation of the map. The resulting scene descreption contains both, objects from the GIS and from the map as well as the relations between them. Fig. 16 shows the architecture of the interpretation system.

In this paper we will focus on the recognition of roads.

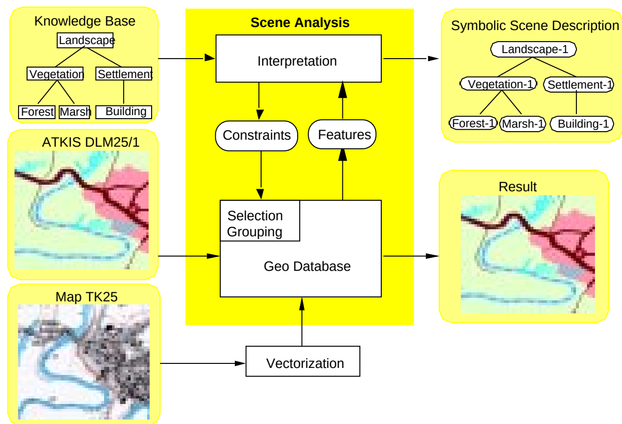


Figure 16: Architecture of the Interpretation System

### 5.1 Input Data and Preprocessing

#### 5.1.1 ATKIS

The a priori knowledge about the landscape 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 all states of the Federal Republic of Germany. Here the Digital Landscape Model (ATKIS DLM 25) 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 ine object class. A more detailed description of the objects is realized by attributes. For instance, an object of the object class road owns 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 node and edges of the road net are not stored explicitly, but the rules for building 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 the object part that is above or below another one.

### 5.1.2 Topographic Maps

The maps to be interpreted are taken from the German official map series 1:25000 (TK25), which is produced for about 100 years. 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. Furthermore morphological operators are used to vectorize the road middleaxes. In the black layer the areas for potential buildings are created. The vectorized and attributed map data is then stored in a GIS, together with the ATKIS data.

### 5.1.3 Connecting a GIS to the Interpretation System

In order to enable the interpretation system to access the ATKIS and map data during the interpretation, a query interface to the GIS is implemented.

## 5.2 Knowledge Representation

Fig. 17 shows a model for roads in the form of a semantic net. In the scene layer the transportation is divided into road traffic which consist of roads. These relations are represented by *part-of* links. In ATKIS a road is simply an ATKIS-Road, which can be obtained directly from the GIS. Because in ATKIS a road is divided into object parts, we describe a road in the map layer as a road segment. The different shapings of a road in ATKIS and in the map are represented by *con-of* relations. Each road segment consists of at least one middleaxis and possibly additional connected middleaxes. The connection is represented by an attributed relation. Furthermore the road segment has two context dependend parts, a left and a right road signature.

## 5.3 Initial Scene Description

To derive an initial scene description from ATKIS data, hypothetical instances are generated top down for all concepts, starting with Transportation. The node ATKIS-Road has a data function, which returns exactly one free ATKIS-Road object from the GIS. If the function successfully returns an object, the status

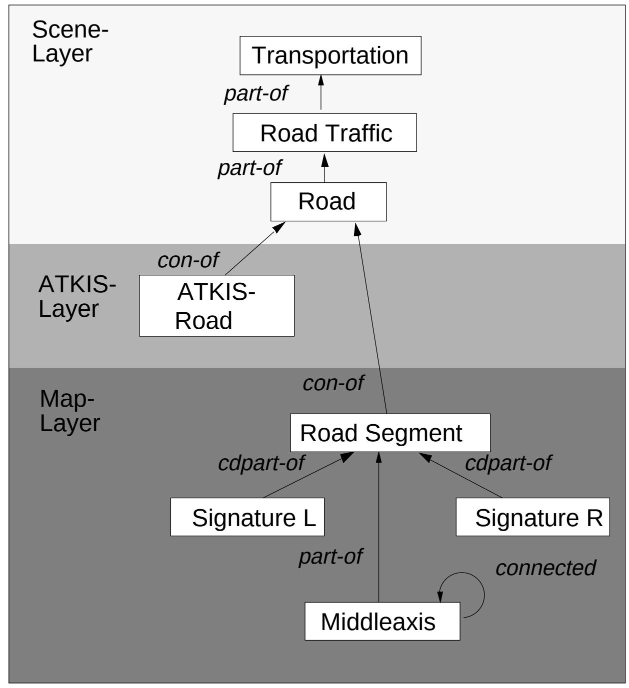


Figure 17: A Model for Roads

of the instance changes from hypothetical to complete. The properties of the ATKIS-Road are propagated bottom up to the node Road, and its status is also changed to complete instance. In this way we get a complete scene description, which contains all road objects from ATKIS.

## 5.4 Extracting Roads from the Map

In a second step the interpretation is extended to map objects. Starting with Road, hypothetical instances for Road Segment and Middleaxis are generated. The properties of the node Road, which were obtained from ATKIS-Roads, are propagated top down. The node Middleaxis has a data function which uses these properties to query the GIS for a matching middleaxis from the vectorized map primitives.

In the GIS the geometry of the corresponding ATKIS-Road is used to create a search buffer. Within the buffer all vector primitives that match certain criterion like width, colour and angle are selected. In order to avoid competing hypotheses, the longest matching segment is returned and the status of the node Middleaxis is changed to complete instance. The attributes of Middleaxis are propagated bottom up and the node Road Segment is changed to partial instance, because not all necessary parts have been found until now.

Afterwards a hypothetical instance for a Middleaxis which is connected to the first Middleaxis is generated by the attributed relation. Again a data function is used to access the GIS and to return a middleaxis that is inside of the buffer and is connected with the previous one. Because due to overlapping signatures there may be gaps between the segments, a middleaxis is regarded as connected when it is located within a maximum distance and the angle between the segments does not exceed a given limit. The values depend on the type of the road. If more than one middleaxis matches the criterion all of them are returned and competing instances are created.

When all Middleaxes for a given Road Segment have been returned, the geometry of the Middleaxes is used to find matching Signatures with the corresponding procedure. When both Signatures could be assigned, the Road Segment is marked as complete instance, otherwise its status is changed to missing instance.

## 6 CONCLUSION

In this paper a system for image interpretation and its application for the interpretation of moorland areas and maps was presented. The kernel of the system is a knowledge based image interpretation system, which uses semantic nets for the explicit formulation of prior knowledge about the objects in the scene. The knowledge is structured hierarchically and represents expectations about the appearance and relationships in the images to be analyzed. The knowledge based system is able to integrate GIS data and to analyze multitemporal images.

The expectations of the interpretation system can be transformed into a task description for a self adaptive image processing system. An agent based system selects a suitable image processing operator, initializes and adapts the parameters of the operator iteratively until the segmentation results coincide with the given task description. Attributes of the segmented image primitives are used to define the goals and to measure the quality of the adaption process. The agents cooperate with each other to find the most suitable agent to solve the given problem. By storing a success statistic they learn their suitability for the current task and the according initial parameters.

The system was sucessfully tested for the interpretation of moorland areas. The segments given by a biotope map were interpreted correctly in CIR images. Comparable results for greyscale images improved that texture is more significant for the classification than colour. For a more precise and differentiated interpretation a multitemporal approach has been applied, using knowledge about the most probable state transitions over the time.

The system was also employed for the interpretation of topographic maps, where roads and buildings have been extracted. A scene description derived from a GIS is used to find matching roads in the map. The recognition of buildings is performed data driven, because they are currently not mapped in the GIS.

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