Knowledge Based Moorland Interpretation using a Hybrid System for Image Analysis

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ABSTRACT

For the automatic interpretation of remote sensing data prior knowledge about the properties of the scene objects, such as form, size and texture, can be used to derive 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.

In this paper we present an approach for a hybrid image interpretation system. It consists of 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.

The presented system is used for the interpretation of moorland in aerial images. The prior knowledge about the different land use states is formulated in a semantic net and used to control the interpretation process. The results show that the approach is suitable for this task. Furthermore we suggest a concept for the extension to a multitemporal interpretation of moorland, where temporal constraints are formulated in a state transition diagram and exploited to improve the monitoring. For the resegmentation of the moorland the adaptive image processing system is used.

1 INTRODUCTION

Nowadays protection of the environment is a problem of ever growing importance, especially in environmentally sensitive regions with industrial activities. One of these regions is moorland. Germany has several moor areas. In order to protect them people working on moor areas must observe certain conditions, according to law. Some areas may only be cultivated during fixed periods, which are determined by administrative authorities. Thus it is obvious, that control of the activities in moor areas is required. As these areas are very large and mostly unfortified, control measurements on the ground are expensive and difficult to obtain. Hence remote sensing is a suitable solution. As the automatic interpretation of moor areas needs a higher resolution than provided by satellite images, aerial images are used for this task. The usual approach for such problems were data driven multispectral classification methods up to now.

But 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. For this reason a modern system for image analysis must 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 multiple sensors and 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 segmentation process and for the interpretation of the segmented image features. Because the image data vary in sensor type, accuracy, illumination, and noise the quality of the segmentation results changes from image to image. For each segmentation process specific parameters of the algorithm have to be adapted to the data. To avoid manual interaction a self-adaptive image processing module should be aimed at.

The combination of two or more modules with different representation languages and inference techniques is known as a *hybrid system*. The subsystems are connected semantically and they influence each other using common interfaces. The presented hybrid image interpretation system consists of two subsystems, the *knowledge based image interpretation system* AIDA and an adaptive image processing system. AIDA generates a symbolic scene description by assigning semantic meanings to segmented image primitives. Similar to the system ERNEST (Niemann, 1990) 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 cues from multisensor and multitemporal images.

For the segmentation of the image data an *adaptive image processing module* based on agents 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.

The concepts of the two subsystems are described briefly in the following sections. The use of the knowledge based system for the interpretation and monitoring of moorland areas is treated in section 4.

2 KNOWLEDGE BASED INTERPRETATION SYSTEM

For the automatic interpretation of remote sensing images the knowledge based system AIDA [(Liedtke, 1997),(Tönjes, 1998)] 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.

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 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.

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. The range 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.

The relations between the objects are described by edges or links forming the semantic net. 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. 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 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. 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. The control knowledge is represented explicitly by a set of rules. 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. 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. Attribute values are transformed 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.

2.3 Extension to multitemporal images

Currently the system is being extended for the interpretation of 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.

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* and describes autonomous working units (Newell, Simon 1972). The task of the agent system is here the automatic parameter adaptation for remote sensing data interpretation. The semantic net supplies a task description formulating the goals for the image processing operator and information about the images used. The goals refer to the quality of the image processing results e.g. the quality of the segmented areas. Necessary informations about the image are for example size, 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 to be carried out.
In the following, the design of the agent system and the parameter adaptation for the image operators is presented. The information required for adaptation and its connection is described more precisely. 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 hierarchical blackboard system (Fig. 1). This means that all agents of one agency *see* the same information at one time on the blackboard.
The interface to the semantic net is realized by the uppermost agent. The agents on the bottom are connected with the image processing operators. The intermediate levels of the agents structure the different image processing fields and also allow the distribution of a task into several partial tasks. This structure is also necessary to add pre- and/or post processing facilities to an image processing operator. In this way the user can integrate new operators into the system more easily and form the construction of the system neatly.

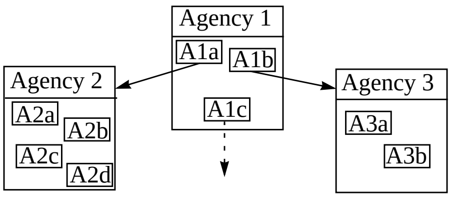

Fig. 1: Agencies with own blackboards

In addition the described structure limits the communication between the agents to a group with identical qualities. The agents can be characterized as knowledge-based and learning and therefore as social agents.

3.2 Adaptation

The adaptation of the parameters for the image processing is based on the iteration shown in Fig. 2. The image processing operator is applied to the input image with the predefined start parameters. 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. The used rules must be given from the user for each operator. This iteration continues until the optimal result has been found (Rost, Münkel, 1998).

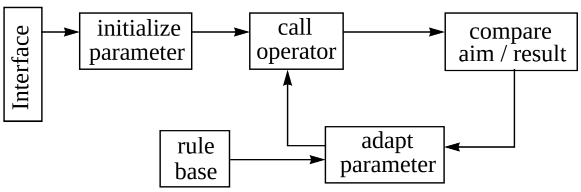

Fig. 2: Parameter adaptation

The combination of an agent and an image processing operator is explained more precisely. The set of possible goals consists of given values for the attributes of the extracted regions. These are:

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

These measures are modelled 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 more narrowly a range is specified, the more important the attribute is.
To describe a result image the attributes of the individual areas are averaged or only the best area for the adaptation is used. In this way for example the following tasks can be formulated:

1. find a round area whose surface should be within a default range.
2. segment the image such that the found areas are as rectangular as possible (man made) and their size exceeds a minimum size.

3.3 Cooperation

Cooperation means to process a task in common (Albayrak, 1993). This cooperation is implemented as a contract negotiation in which the agents giving the order negotiate with potential receiving 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 which are unsuitable for the task are excluded from the following negotiations.
2. The remaining agents are given information about the goals of the operation and information about the data. Then the agents estimate their suitability to solve the task.
3. In the last step, one or more agents are instructed to process the task.

3.4 Learning

The basis of the learning procedure is the above mentioned set of negotiation functions between the hierarchically structured agents. The aim of the learning procedure is to organize the behaviour of the agents in such a way that the task which is 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. On the one hand the selection of a suitable image processing operator for the task and on the other hand 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 and the previously mentioned credit values.

If an operator 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 the initialization of the parameters for this task the stored ones from the most similar task are used as start parameters.

4 INTERPRETATION OF MOORLAND IN AERIAL IMAGES

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 section 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 4.5.

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. [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 color 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. 3 shows a simplified version of the concept net.

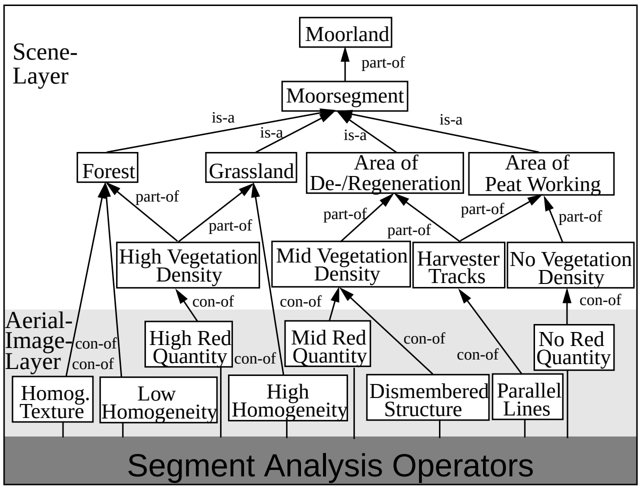

Fig. 3: Concept net for the interpretation of moorland

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 in Fig. 3 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 colors to be looked for, if a state is to be allocated to a segment. At the bottom of Fig. 3 *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.3 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

In Fig. 5 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. 4) 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.

Fig. 4: Aerial image of the used test area

A second interesting result of the interpretation is reached, 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. 3 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. 5. The misinterpreted segments were mostly small, narrow or not typical for the land use states. This result shows, that color information brings in fact additional information, but for most unproblematic regions texture information is sufficient.

Fig. 5: 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. 6.

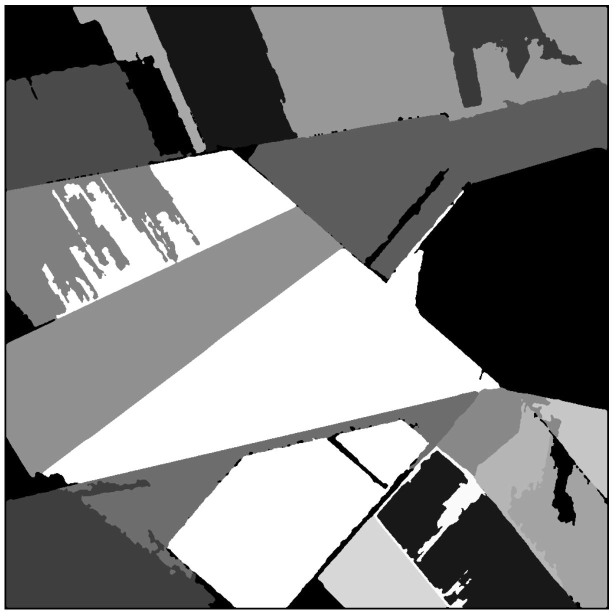

Fig. 6: Segmentation result using *Split and Merge*

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

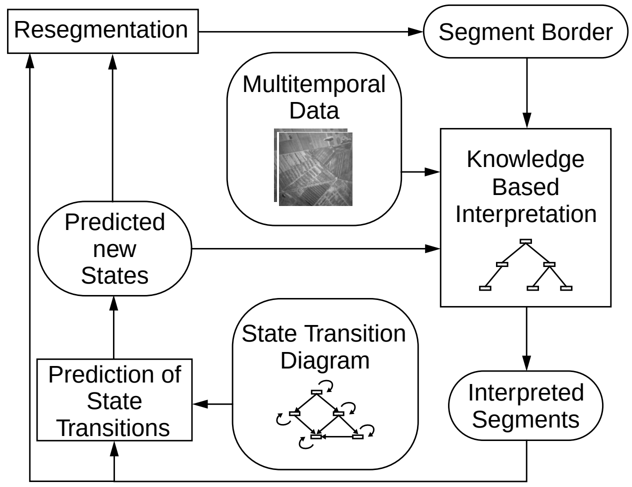

Fig. 7: Concept for a multitemporal moorland interpretation

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 shall later 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 as the predicted new states and the multitemporal data.

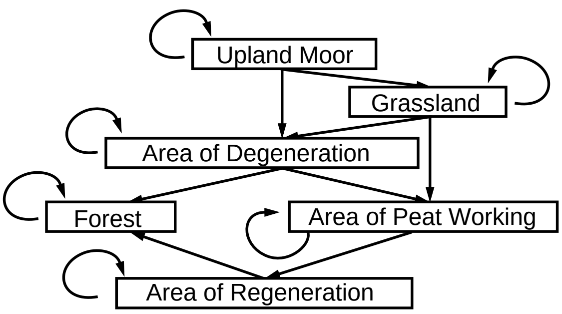

Fig. 8: State transition diagram for moorland developement

The *state transition diagram* in Fig. 8 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. In contrast to the concept net in Fig. 3 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. Here this means that if there is 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 certainty. The certainty describes the probabilities of the state transitions. This value affects the order in which the different state transition hypotheses will be verified. As shown in Fig.8 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.

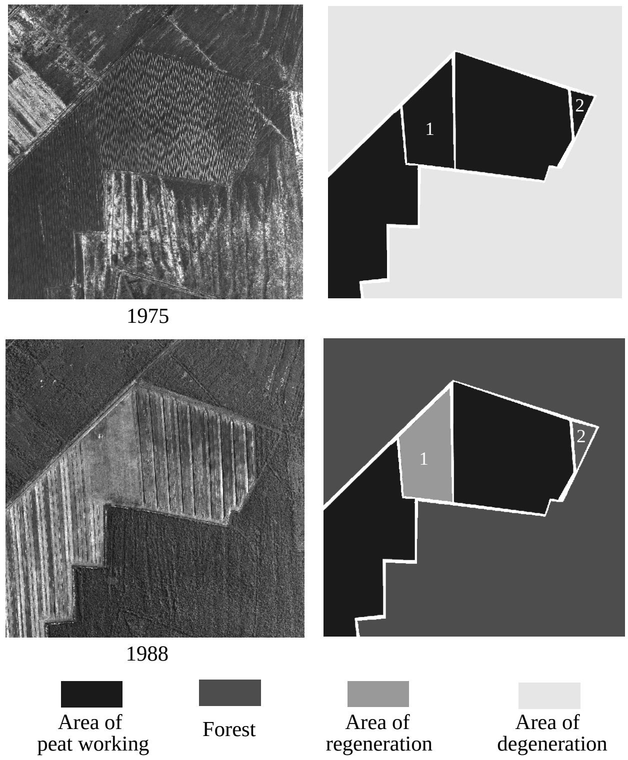

Fig. 9: Usage of state transition diagram for multitemporal interpretation

In Fig. 9 a result of the usage of the *state transition diagram* is shown for two grayscale aerial images taken at two epochs. The aerial images were divided into five segments. For every segment the system determined the state transition. The semantic net we used for the multitemporal interpretation is a refinement of Fig. 3. In addition to the seperation 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.

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. 7. 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 3. 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. Belonging to the values of certainty 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 CONCLUSIONS

In this paper a hybrid system for image analysis and its use for the interpretation of moorland areas was presented. The system consists of a knowledge based image interpretation system which uses semantic nets for the formulation of prior knowledge about the scene objects. The knowledge is structured hierarchically and represents expectations about the appearance and relationships of objects and their parts in the images to be analyzed. The knowledge based system is able to integrate GIS data and to process images from multiple sensors. The system was extended to realize a multitemporal interpretation by using state transition knowledge.

The expectations of the semantic net are 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 adaptation process. The agents cooperate with each other to find the most suitable agent to solve the given problem. By storing their success they learn automatically their suitability for the current task and the corresponding initial parameters.

The knowledge based system was used successfully for the interpretation of moorland areas. The segments given by a biotope map were interpreted correctly in CIR images. Comparable results for greyscale images proved that texture is more significant for the classification than colour. The results of the used approach for multitemporal interpretation show that some land use states can not be interpreted without the used state transition knowledge.

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