KNOWLEDGE BASED INTERPRETATION OF MOORLAND IN AERIAL IMAGES

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ABSTRACT

For the interpretation of remote sensing data the traditional methods such as multispectral classification are in many cases not sufficient. This applies especially to more complex scenes. In order to interpret such scenes it is necessary to include and use more prior knowledge about the depicted objects, e.g. knowledge about the possible object structure or, in a multitemporal interpretation, knowledge about the possible temporal changes.
In this paper we present an approach for the automatic interpretation of moorland from aerial images. The first step is a monotemporal interpretation. We use a knowledge based system with an explicit knowledge representation through semantic nets. This system is suitable to formulate explicitly (i.e. in a standard language) prior knowledge and to use it for the interpretation. In our case we divided moorland into different relevant land use classes and described them in a semantic net. For every class we described the obligatory parts. Obligatory parts are features and structures, which have to be detected in the particular areas in order to assign them the corresponding class.
Because in moorland areas monitoring of changes is very important we extended the monotemporal system to a multitemporal one. The multitemporal interpretation also exploits explicitly represented prior knowledge about the possible temporal changes.
The results show that the presented approach is suitable for the interpretation of moorland. The exploited additional prior knowledge led to an improvement of the interpretation, especially for the multitemporal one.

1 INTRODUCTION

Monitoring of moorland is necessary, because this area is both an environmentally sensitive region and also of interest for industrial work. One way to accomplish this task is to use remote sensing techniques. In multispectral, moorland is sometimes detected, but often appears as just one single class. At a closer look, however, a moor area consists of regions with quite heterogeneous use.

In this work we present an approach for an automatic knowledge based and rule based multitemporal interpretation of moorland. Up to now the usual methods for an interpretation of such areas were data driven multispectral classifications (e.g. NMU (1997)). But standard multispectral classifications don't use prior knowledge about the area to be interpreted. For moorland such prior knowledge is for example the fact that peat extraction is performed mostly by using harvester machines. Theses machines leave visible tracks on the ground which can be recognized as lines in the related images. The use of prior knowledge has the potential to improve the interpretation because it reduces the search space by additional constraints.

Our interpretation is divided into two parts: The first part is the monotemporal interpretation and uses only information regarding geometry, radiometry and texture of the land use classes. The second part is the extension to a multitemporal interpretation. The necessary temporal information for this part is formulated in a diagram, which describes the most probable state transitions. In the monitoring process the state transition diagram is used to predict the possible land use changes. This leads to a reduction of the search space and improves the monitoring.

In the next section we briefly describe the knowledge based system we used for the interpretation. In section 3 the prior knowledge we used for interpretation of moorland and in section 4 an overview about the recognizability of moorland classes is given. Section 5 describes the interpretation process: After the description of the used input data (5.1) and a concept for an initial segmentation of the image (5.2) the monotemporal interpretation process together with the obtained results will be shown in section 5.3 and the extension to the multitemporal interpretation is demonstrated in section 5.4. Section 6 concludes the paper and gives an outlook for further research.

2 KNOWLEDGE BASED INTERPRETATION SYSTEM

The system used for the presented approach is the knowledge based system AIDA (Liedtke et. al. 1997, Toenjes 1998) which was developed in order to automatically interpret remote sensing images. The system strictly separates the control of the image analysis process from the semantics of the scene. The knowledge representation is based on semantic nets (Niemann et. al. (1990)). Semantic nets are directed acyclic graphs. They consist of nodes and edges in between the nodes. The nodes represent the objects expected in the scene while the edges or links of the semantic net model the relations between these objects. Attributes define the properties and methods of nodes and edges.

The nodes of the semantic net model the objects of the scene and their representation in the image. Two classes of nodes are distinguished: the concepts are generic models of the 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 composed of concepts. During the interpretation a symbolic scene description is generated consisting of instances.

The relations between the objects are described by edges or links of the semantic net. The specialization of objects is described by the is-a relation introducing the property of inheritance. Along the is-a link the description of the parent concept is inherited to the more special node which can be 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 for structuring the knowledge in different conceptual layers, for example a scene layer and an image layer.

To make use of the knowledge represented in the semantic net control knowledge is required which states how and in which order the image interpretation 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 completely instantiated. If an obligatory subnode could not be detected, the parent node becomes a missing instance. The control of interpretation is also performed by an A*-Algorithm. For further details see Toenjes (1998).

For the interpretation of multitemporal images the system was extended by temporal relations. They realize the use of temporal knowledge which is described in *state transition diagrams* (see section 5.4). 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.

3 PRIOR KNOWLEDGE

In this section an overview of the prior knowledge about moorland is given (see Redslob (1999), Eigner (1991),Göttlich (1990) for further details). This knowledge will be implemented in the knowledge base for the monotemporal interpretation (see section 5.3) and the multitemporal one (see section 5.4). With the example moorland interpretation the way from the general knowledge described below to the explicit representation form which is used in our approach and which can be processed by the knowledge based system is demonstrated.

Originally, moors were upland moors. In Germany these have practically vanished. Today mostly agriculturally used areas, forests and areas of regeneration or degeneration are found in the former upland moors. The most important industrial use of moorland is the peat extraction. In order to make peat extraction possible in a moor the ground has first to be drained. Therefore ditches need to be created. Thus, the water level goes down and the area begins to degenerate. The vegetation changes. During the state of degeneration the vegetation is inhomogeneous and irregular. Then, peat extraction is possible. Usually harvester machines are used. In aerial images the use of the machines can be recognized by parallel tracks. After peat works have finished, a regeneration of the moorlands can begin. In most cases people simply stop working the land and leave it to regenerate, which eventually results in increasing vegetation. Hence, in this state of land use vegetation can be found again on these areas, especially birches because of the dry ground. In many cases also remains of the tracks from the harvester machines from the state before can still be found. In order to start up a regeneration in the direction of the original state, upland moor, sometimes supporting steps are being carried out. Such steps can be to fill up the ditches und to remove trees in order to reach a raising water level, which is one prerequisite for the goal. If the water level does rise trees out die and a homogeneous vegetation without trees grows.

4 RECOGNIZABILITY OF DIFFERENT MOORLAND CLASSES

In order to recognize different classes in moorland areas an investigation about the recognizability of moorland classes has been carried out (Suffrian 1999). As input data analogue CIR-aerial images with an image scale of 1:10000 in the “Tote Moor” near Hanover were used. The task was to investigate, which moorland classes can be distinguished from the given images by human operator. The visible differences between the classes could be differences in color information just as differences in texture, structure and form.

As mentioned the aim of our research is to realize a system for the automatic interpretation of moorland. In order to estimate which moorland classes can be distinguished automatically by the system, we assume that the upper limit of classes can be estimated by the number of moorland classes, which can be distinguished interactively by an experienced human operator. That means that in our opinion the judgment if a moorland class can be recognized automatically by a system requires in any case the recognizability by an experienced human operator in the same input data. There is one exception from this assumption: If the input data consist of many spectral bands, which usually can be handled better by computer systems than by human operators. But this case applies not for the used input data.

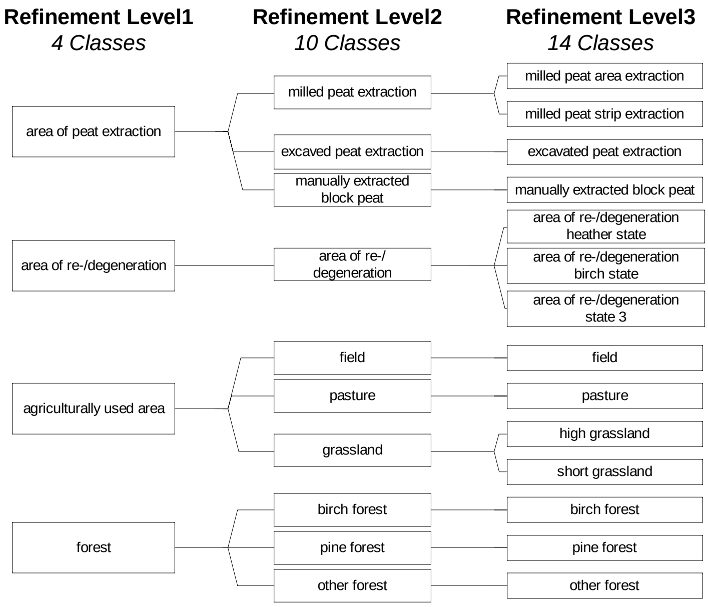

Figure 1. Recognizable moorland classes

During the investigation as a first step the operator began to distinguish between all areas which show visible differences. The result of this step were forty different classes. Then, an accumulation of classes, which belong together was performed. The result can be seen in Fig.1.

For a better estimation which of the classes can be recognized automatically the moorland classes were included into three lists with three levels of refinement. The first level shows the classes, which can be distinguished and recognized very well. The third level with highest degree of refinement shows the classes, which have in some cases only fine differences in the features.

The interpretation system described in section 5.3 is based on the classes in refinement level 1. As shown in Fig.1 a distinction between an area of regeneration and an area of degeneration is very difficult, because the vegetation is similar. A distinction can be performed by using temporal knowledge for the interpretation of multitemporal data as shown in section 5.4.

5 MOORLAND INTERPRETATION

5.1 Input Data

Our test area is the moor area in the northwest of Hanover near Steinhude in Lower Saxony. We work with aerial images with a resolution of 0.5m/pel. The main input sources are CIR-images (from July), but we also tested the results with grayscale images. The reason is that although color images contain more information, most available aerial images are grayscale images. Also, for the multitemporal approach which is described in section 5.4 we used grayscale aerial images from different epochs.

The second input source is a segment image. The segment image masks the different segments of the aerial image, which is to be interpreted. The segment image can be based on a biotope mapping. Biotope mappings were performed for many moorland areas in Germany by ground survey. For regions without biotope mapping we show in section 5.2 a possible initial segmentation method which uses GIS information as prior knowledge.

5.2 Initial Segmentation

The assumption that a biotope mapping exists does not apply for every area. For some areas an automatic initial segmentation is necessary instead. A view on the aerial images of moorland shows that there are many spectrally inhomogeneous areas. Because some moorland classes consist of inhomogeneous areas a simple multispectral classification is not suitable for segmentation. The segmentation process is depicted in Fig.2. It requires CIR-aerial images. In the case of grayscale images a biotope mapping or a manually created segmentation is necessary.

The most important information for the segment borders in moorland are the streets and the main ditches. This information can usually be extracted from the GIS database, e.g. from ATKIS Basis DLM. Based on this information an initial segmentation is performed. The knowledge exploited for the segmentation is the same used in section 5.3. The next step is to refine the initial segmentation: Inside every segment the normalized difference vegetation index (NDVI) is computed and the regions with high density of vegetation index and also with very low density were extracted. For every extracted subsegment the form parameter compactness is computed. Only subsegments with high compactness and a minimum area size are accepted as valid regions for the final segmented image. Fig.5 shows the result of this procedure for two parts of the test area.

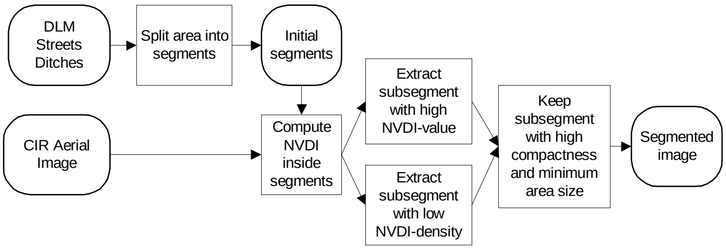

Figure 2. Initial segmentation of moorland

5.3 Interpretation

This section describes the monotemporal interpretation of moorland from aerial images. As described in section 2 the system we used for this work needs the prior knowledge in the explicit representation form of semantic nets. Therefore, the prior knowledge about the relevant area is formulated in a concept net. Fig.3 shows a simplified version of this net.

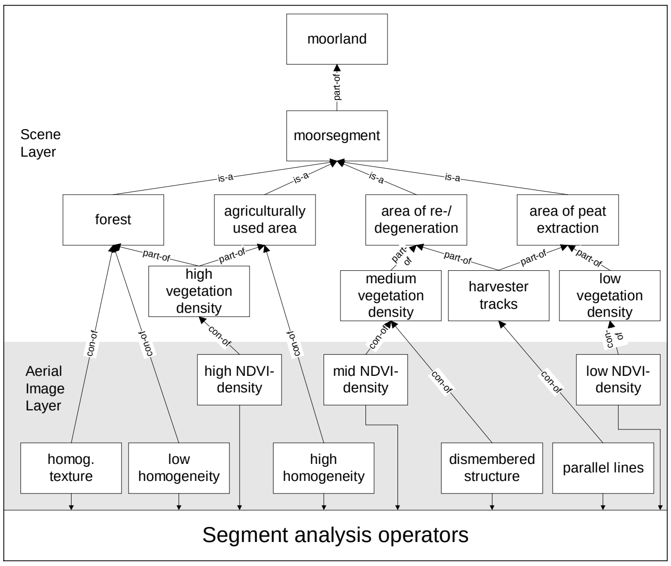

Figure 3. Concept net for the interpretation of moorland

Based on section 4 we distinguish four states of moorland classes: *forest*, *agriculturally used area*, *area of re-/degeneration* and *area of peat extraction*. 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 extraction* is characterized by *harvester tracks* and *low vegetation density*. The state *area of re-/degeneration* is also characterized by *harvester tracks* in one part, but also by *mid vegetation density*. The nodes in the second layer, the *aerial image layer*, describe the depiction of the scene layer nodes in CIR aerial images and their properties. The nodes describe the structures and colors to be looked for, if a state is to be assigned to a segment. Thus both color and textural information are used. That's why the concept net is suitable for both color and grayscale images (see below). 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 *segment analysis operators* have to verify the meaning of the node for a particular segment. This means that they look inside a given segment and estimate whether the hypothesis of the node is correct or not. In this way the operators transform the explicitly formulated hypothesis into image processing operations. Only on this level the interpretation has direct access on the raster images. E.g. the operator connected with the node *dismembered structure* analyses the structure of the edges in a particular segment. Short and curved lines lead to better assessment than long and straight lines.

During the interpretation an instance net is created. With the concept net as prior knowledge hypotheses are created and verified in the instance net. At the end of the process the instance net shows which parts of the concept have been verified correctly. Therefore, the instance net contains at the end a description of the scene. The creation of nodes in the instance net is called instantiation. The instantiation starts with a predefined seed node. 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. To show the instantiation process in our case, it is described in the following. Here the instantiation process starts with the creation of a hypothesis of the concept *moorsegment*. At this point one segment is taken from the segment 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 extraction*: A concept node *area of peat extraction* is created. Two obligatory parts of this node have to be present: *harvester tracks* and *low vegetation density*. This leads to the top-down instantiation of the concept *harvester tracks* along the *part-of* relation. The concretization 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 answers back whether parallel lines were found or not. If the result is positive the operator returns a certainty value to the node, which describes the quality of the result, and 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 extraction* is be verified and for the second verification also a certainty value is determined. Now all obligatory parts of *area of peat extraction* are present and the node is instantiated completely. Also a certainty value for this node is 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. In Fig.5 the result of the interpretation based on the initial segmentation (section 5.2) and on the CIR aerial image of the test area (Fig.4) is shown. Results based on biotope mappings are depicted in Pakzad et. al. (1999). The result of the interpretation reveals, that most segments were interpreted in the same way as a human operator would interpret them using only the aerial image. The misinterpreted segments were mostly small, narrow or not typical for the land use states. Using grayscale aerial images instead of a CIR in led to similar results (see Pakzad et. al. (1999)). This result shows, that while color information in general contains additional information, for most unproblematic regions texture information is sufficient for the interpretation.

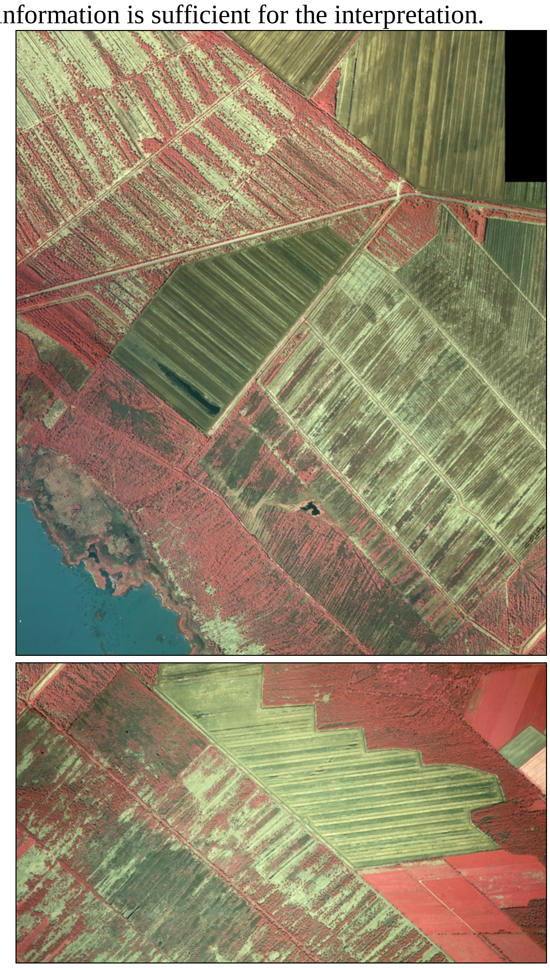

Figure 4. Aerial images of the used test area

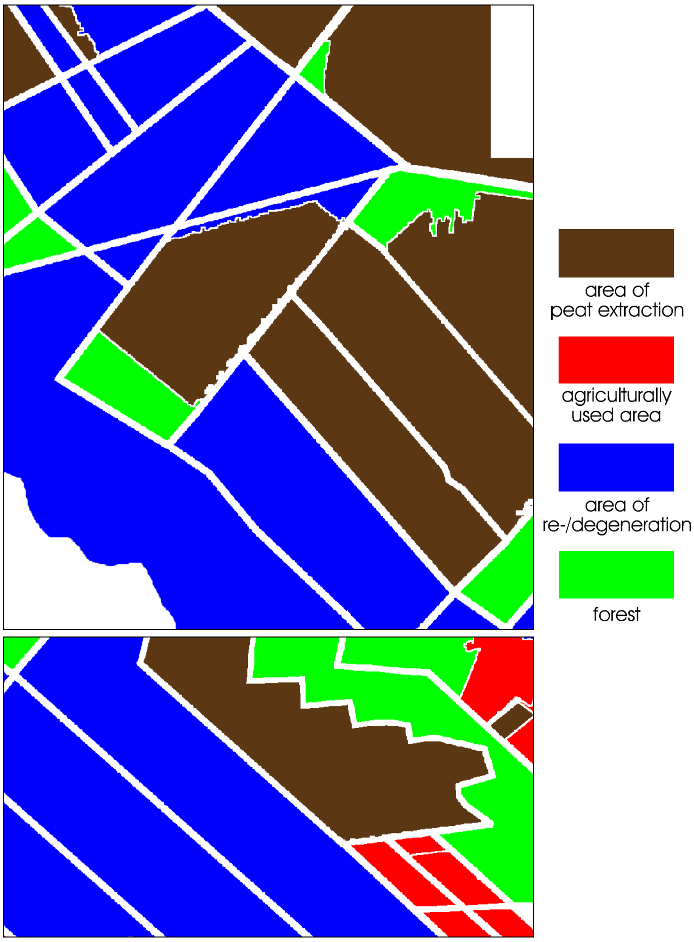

Figure 5. Interpretation result

5.4 Multitemporal Interpretation

In this section we describe the extension of the system described so far to a multitemporal interpretation system. This is necessary for our application because besides the assignment of classes to areas in moorland the monitoring of changes is very important.

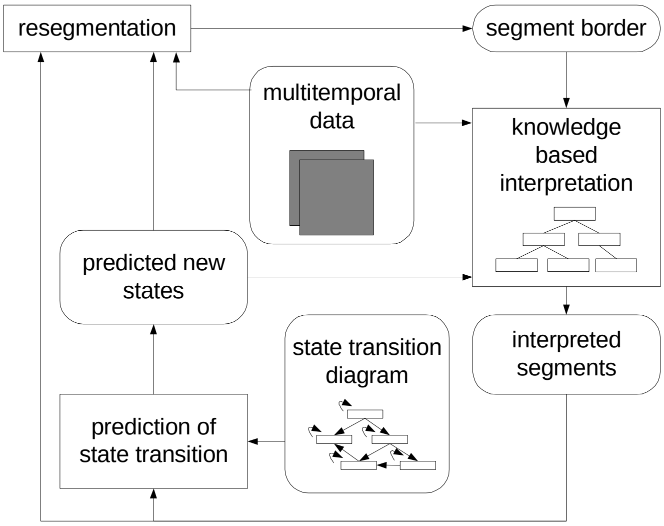

Figure 6. Concept for multitemp. moorland interpretation

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 based on the results of the interpretation before. These results restrict the search space and hopefully lead to an improvement of the monitoring process.

Fig.6 shows an overview of the system structure. 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.

The borders of the segments may change between the interpretation intervals. Therefore, for the multitemporal approach we include a module to perform segment splitting by segmentation. The approach is described in Pakzad et. al. (1999) and uses 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.

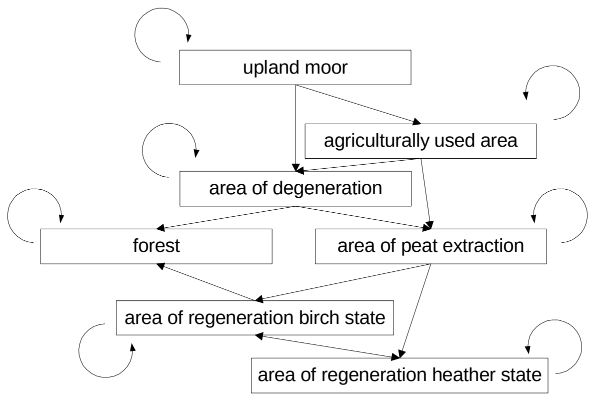

Figure 7. State transition diagram

The temporal part of the prior knowledge described in section 3 is implemented in the *state transition diagram*, see Fig.7. It describes the most probable state transitions. Although many more state transitions are possible there are restrictions by law and nature, and we can use these restrictions in order to improve the interpretation.

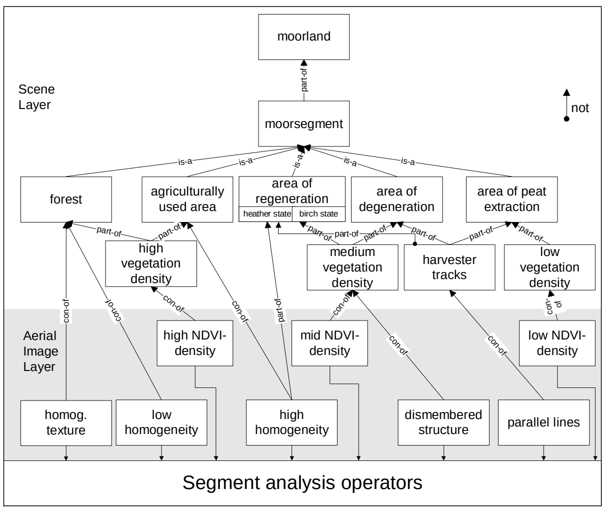

Figure 8. Extended concept net for multitemporal interpretation

In contrast to the concept net in Fig.3 this diagram contains seven 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. In addition the state *area of regeneration* is also divided into two parts: *birch state* and *heather state*. As mentioned in section 4 the distinction between the states *area of degeneration* and *area of regeneration* in aerial images taken at one epoch 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 extraction* the system knows, that this segment has passed the state *area of degeneration*, and if in a new epoch a *segment analysis operator* finds for example vegetation, the only possible states are *area of regeneration* and *forest*. This prior knowledge enables also the distinction between the two regeneration states. If no more *parallel lines* can be found on an area which was used before for peat extraction and if the system finds homogeneous areas, the system expects that there are no more ditches in order to dry the ground (see section 3) and the requirement for the state *area of regeneration heather state* is correct (*heather state* is not defined as an area on which already heather is growing but as an area which is changing toward the state).

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.7 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.

The semantic net we used for the multitemporal interpretation is a refinement of the net in Fig.3 and is depicted in Fig.8. It contains the separation into the states *area of degeneration*, *area of regeneration birch state* and *heather state* with their obligatory parts. The probabilities depend also on the time differences of two epochs.

For a part of the test area the multitemporal interpretation was performed. As input data three grayscale aerial images taken at the epochs 1969, 1975 and 1988 were used. The first image from 1969 was the basis of the initial segmentation, which divided the image into three segments. For every segment the system determined the state transition. Fig.9 shows the result.

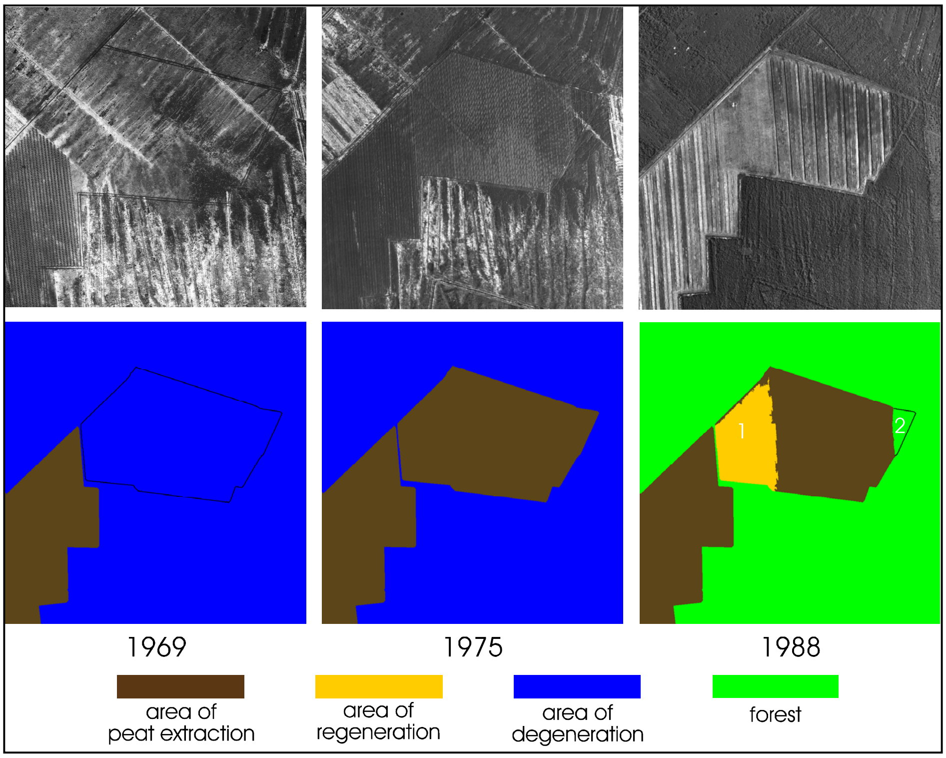

Figure 9. Result of multitemporal interpretation

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 extraction* to *area of regeneration heather state* is stated using the knowledge about the previous land use of the segment and about the missing parallel lines. Without using this prior information the system could not distinguish the states *agriculturally used area* and *area of regeneration heather state* 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 extraction* to *forest* although there is no direct state transition between them represented in the *state transition diagram*. Due to the rather long time interval of 13 years between epoch t+1 and t+2 the regeneration states were not observed. Using the knowledge about the mean transition times the system also generated the hypothesis for *forest* which was verified successfully for segment 2. The transition state between 1975 and 1988 was with higher probability the state *area of regeneration birch state*, because this is the direct way between the two states *area of peat extraction* and *forest*. But it is also possible that the area changed first to the state *area of regeneration heather state* and after that to the other two states.

The exploitation of the *state transition diagram* is reached through an extension of the semantic net in Fig.8. The semantic net used for this purpose takes advantage of temporal links in addition to the other one. These links are 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 are created along the temporal links. These hypotheses exclude each other. According to the priorities the verification of the different *state transition hypotheses* is processed in a particular order. The search tree splits. 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 epoch t+1 all instance nodes of the interpretation for the time t will be removed, and the interpretation will continue for epoch t+2 in the same way.

6 CONCLUSIONS

The current results of the monotemporal interpretation using CIR aerial images led to correct results for the segments of our test area. Applying the interpretation on grayscale images led for the most segments to the same results. This is important because most existing aerial images of such areas are of grayscale type.

The extension to a multitemporal interpretation enables the distinction between more land use classes, which could not be interpreted without the temporal knowledge. This applies e.g. to the distinction between the land use classes *area of regeneration* and *area of degeneration*. The depiction of both classes in aerial images can be very similar. To distinguish between these classes the temporal knowledge, whether peat extraction had been carried out or not, is necessary. The exploitation of temporal knowledge leads to a more robust interpretation of land use classes, e.g. the distinction between agriculturally used area and area of regeneration (section 5.4). The use of temporal knowledge can therefore partly replace the need of color information.

The presented approach was successfully used for the multitemporal interpretation of moorland. The results show that the exploitation of prior knowledge improves the interpretation compared to purely data driven methods. With the presented approach we also show a suitable way to formulate and use the prior knowledge for image interpretation. The explicit knowledge representation allows us to formulate prior knowledge easily in a standard language and also to adapt it to similar problems in a simple way.

The research in this area will continue in different parts: The image processing operators have some parameters which have to be adapted manually to the used images. The aim is to do this automatically. Other parts are the resegmentation and the probabilities of the multitemporal interpretation. Furthermore the suitability of the used prior knowledge for other moor areas has to be verified.

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