3D RECONSTRUCTION OF OBJECTS FROM AERIAL IMAGES USING A GIS*

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ABSTRACT:

The increasing amount of remotely sensed imagery asks for methods that automate the analysis. To deal with the uncertainty and the complexity of the remote sensing data prior knowledge about the objects expected in the scene is used. The presented approach employs semantic nets to represent this knowledge explicitly.In addition to this general knowledge a digital landscape model (DLM) is used which contains the location and some properties of the objects in the specific scene. The interpretation system has an on-line access to GIS database (here: ATKIS DLM 25/1). The system exploits the GIS to hypothesize an initial scene description to be tested in the remote sensing data. Furthermore, the expectations from the GIS are used to control the segmentation algorithms. The system has successfully been applied for the extraction of roads, vegetation (here: forests), and complex structures (here: purification plant and buildings) from aerial images.

1. INTRODUCTION

The analysis of remotely sensed images for environmental and agricultural monitoring represents a major topic of remote sensing. The large amount of data asks for methods that automate the object extraction. However, automatization suffers from two obstacles: the complexity of the scene and the uncertainty of the data. To overcome these problems prior knowledge about the objects must be used to constrain the object parameters and to reduce the uncertainty of the interpretation. The analysis exploits structural relationships of the objects to increase or decrease the reliability of competing interpretations. The interpretation employs data driven and model driven methods.

A lot of scene interpretation systems have been developed in the past. They differ in a number of aspects like the control strategies, the knowledge representation or the application domain. Concerning the representation of the scene knowledge a lot of systems for aerial image interpretation like SPAM [McKeown 1985] employ rules. SIGMA [Matsuyama 1990] is organized in three expert modules using frames and rules. Production rules and semantic nets are found in MESSIE [Clément 1993]. Hartog [96] suggests semantic nets to formulate topological relationships. Quint and Sties [95] use the system ERNEST [Niemann 1990], which is based on semantic nets, to exploit the object structure for interpretation. The presented system AIDA (Automatic Image Data Analyzer) [Liedtke 97] adopts the idea to formulate prior knowledge about the scene objects with semantic nets. In addition the control knowledge is represented explicitly by rules.

Scene analysis assigns an object semantic to the features in the aerial image. For most landscapes a partial interpretation already exists: the map corresponding to the observed scene. The presented system exploits a digital landscape model of a GIS. The GIS provides both, semantics and geometry of the included object classes.

The GIS data may be out of date and incomplete. Hence the object extraction proceeds in two steps. First the GIS is used to generate a partial scene interpretation. Consecutively this interpretation is verified in the aerial image and adapted accordingly. Furthermore, objects not included in the GIS are searched for.

New approaches use manually vectorized maps [Quint, 95; de Gunst 97] or a digital data base [Bordes, 97] to guide the aerial image interpretation. AIDA has an on-line access to a GIS at its disposal which makes the prior interpretation of maps unnecessary.

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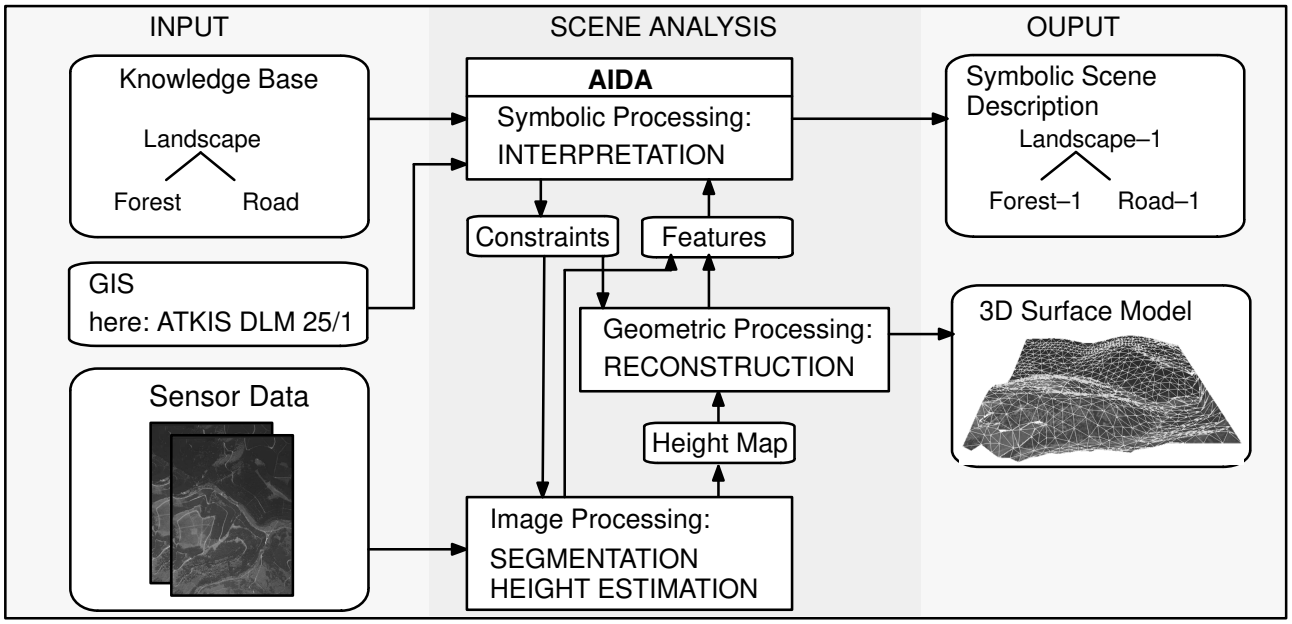

Fig. 1: Architecture of the knowledge based scene interpretation system AIDA

2. SYSTEM OVERVIEW

Figure 1 shows the architecture of the knowledge based scene interpretation system AIDA. The system is designed for the interpretation of images, e.g. aerial images. The prior knowledge about the objects to be extracted from the image data is represented explicitly in the knowledge base. Besides this general knowledge about the objects the interpretation takes advantage of a GIS database. The used German digital landscape model DLM 25/1 of ATKIS (Authoritative Topographic Cartographic Information System) mirrors the content of the 1:25000 map. It contains the 2D geographic location and some selected properties of the objects.

From the GIS a partial interpretation of the scene is derived. However the GIS my be out−dated. Hence the partial interpretation constitutes a hypothesis which must be tested in the sensor data by generating constraints for the features expected in the image. The image processing module extracts line shaped and areal features from the aerial image that meet the constraints given by the interpretation module. It returns the found features and a reliability measure. The interpretation module groups the features, evaluates the relationship between the features to decrease or increase the reliability of competing interpretations, and generates new hypotheses for image features. Using this mixed top−down and bottom−up strategy the system generates a symbolic description of the observed scene.

For reconstruction of the 3D geometry a height map is computed from overlapping aerial images using stereo matching techniques. This height map is used by the reconstruction module which approximates the objects by parametric surface models. The appropriate surface model is constrained by the interpretation module which selects blocks, cylinders, smooth three dimensional surfaces, etc.. For visualization the surfaces are approximated by a triangular mesh with overlaid photo texture.

The prior knowledge about the objects and their relationship to the feature classes in the GIS and the features in the aerial images is formulated in a semantic net. The next section describes the knowledge representation.

3. KNOWLEDGE REPRESENTATION

The knowledge about the object structure and its relationship to the sensor specific appearance can be represented efficiently by semantic nets. Semantic nets consist of nodes and edges in between. The nodes are implemented as frames which contain a collection of attributes. Furthermore, the object has methods, i.e. functions, at its disposal to compute the attribute values. There may also be a method available to segment the object in the image data. The edges or links of the semantic net form the relations between the objects. AIDA provides a network language, described below, to represent the application specific knowledge. A problem independent control mechanism exploits the semantics of the network language to control the interpretation.

3.1 Knowledge Base for Aerial Image Interpretation

3.1.1Conceptual Layers: Figure 2 shows a simplified semantic net for landscape modelling. The knowledge base distinguishes five conceptual layers. The top layer, called scene layer, describes the scene specific semantic. The GIS layer contains the objects as represented in the GIS. The layers in the middle represent the objects based on their 3D geometry and material respectively. The bottom layer is sensor related and describes the sensor specific photometric and geometric appearance of the objects. According to the chosen sensor (infrared, SAR, or as here visual) a specific sensor layer is used. Each layer possesses a common appropriate vocabulary. For example the scene layer uses a cartographic coordinate system (e.g. Gauss−Krueger) while the sensor coordinate system is referred to the image raster.

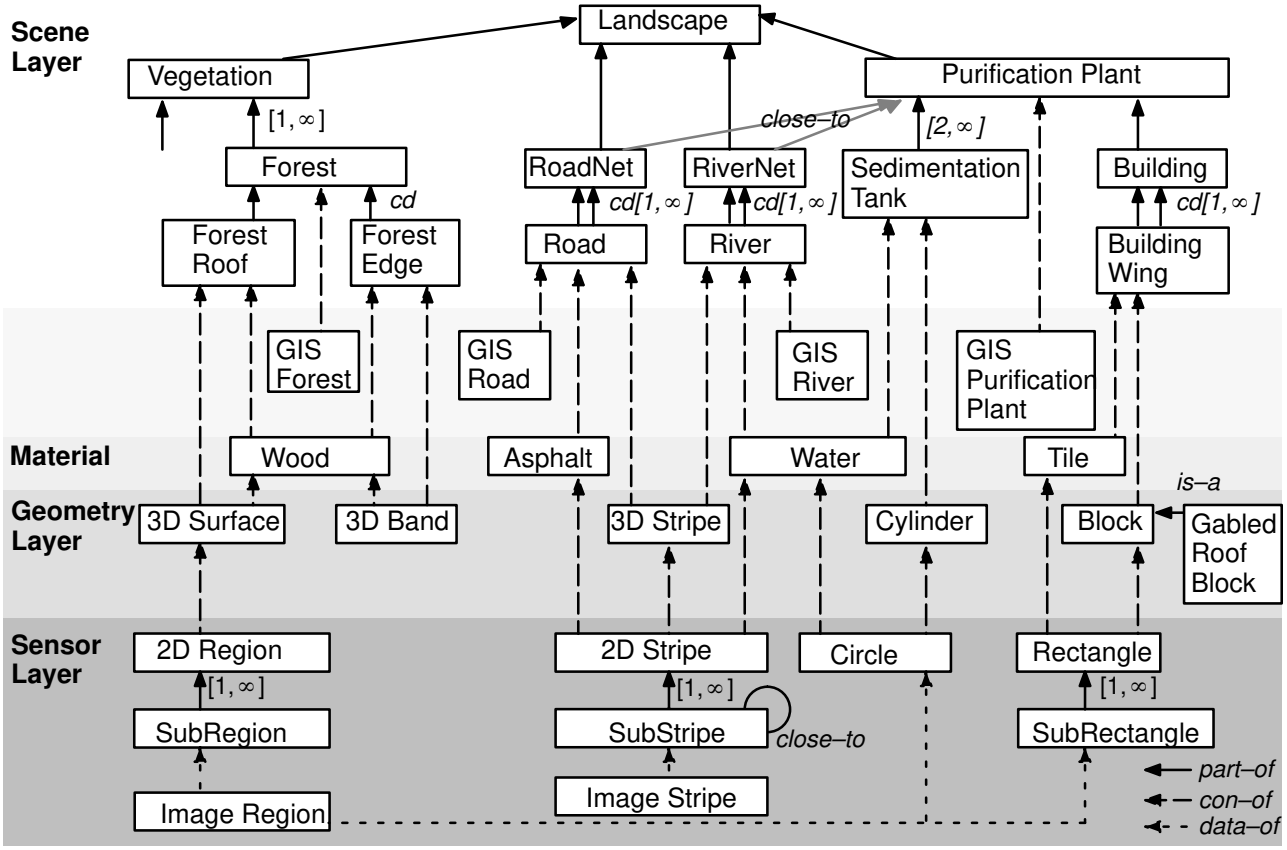

Fig. 2: Simplified semantic net representing the generic landscape model

3.1.2 Network Language: The layer specific level of abstraction is modelled by the concrete−of link, abbreviated *con−of*. The decomposition of an object into its parts is described by the *part−of* link. Here the purification plant consists of at least two sedimentation tanks and one building. Some parts may only be detectable if other parts have already been found and thus established a certain context. These context dependent parts are modelled by *cdpart−of*. For example it only makes sense to search for forest edges in the context of forests. The *data−of* link establishes a relation to the features segmented in the image data. A *data−of* link indicates that the object can be segmented directly in the sensor data by image processing operators.

The specialization of an object is described by the is−a link. This link type introduces the concept of inheritance. First the interpretation will look for the generalization, e.g. block shaped house, before it checks for its possible specialization, e.g. block with gabled roof.

Geometric or photometric relations between objects can be represented explicitly by *attributed−relations*. This link type contains attributes which restrict the attributes of the related object. While the *is−a*, *part−of*, and *con−of* relations propagate information top−down or bottom−up the *attributed−relation* propagates information mainly horizontally. For example a further *SubStripe* of a road adjacent to an existing one can be hypothesized via the *close−to* link in figure 2.

3.2 Control Strategy

The interpretation exploits the generic model in figure 2 to generate a specific semantic net describing the scene represented by the remotely sensed images. While, for example, the knowledge base contains only one generic model of a road, the scene description includes as many roads as detected in the sensor data. Counters in the link of the generic model state the minimum and maximum number of required links in the scene description. The nodes of the scene description, called instances, are linked via *instance−of* to their concept nodes in the generic model.

In AIDA the control knowledge, i.e. the knowledge how and in which order scene interpretation has to proceed, is formulated in a set of predefined rules. An inference engine determines the sequence of rule execution. A rule is composed of a condition and an action part. The condition checks for a new interpretation state of neighboured nodes in the semantic net. The action part generates a new hypothesis or adapts the interpretation state of the focused node accordingly. Furthermore the attributes are computed based on the new information.

The current scene description is stored in a search node which contains all concepts and instances with their interpretation state. If competing interpretations occur the search node splits into child search nodes. The leaves of the resulting search tree represent all currently possible interpretations. Each search node is judged by summarizing the judgements of all included instance nodes. An A*−algorithm selects the most promising search node for further investigation. The interpretation process stops if a complete instance of a predefined goal concept was generated. For a more detailed description the reader is referred to [Liedtke, 97] [Pakzad, 97].

4. GIS BASED PARTIAL INTERPRETATION

4.1 ATKIS

With the development of geo information systems more and more geo data becomes available in digital form. In Germany, for example, the state ordnance surveys developed the 'Authoritative Topographic Cartographic Information System (ATKIS)' (Grünreich, 92). In the presented work the digital landscape model DLM 25/1 is used which mirrors the contents of the 1:25000 map and is available for most parts of Germany.

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

The objects are composed of parts which contain the geometric information. The geometry is described by points, lines, or regions. The object parts my also possess specific attributes like the width of a road. In contrast to maps the DLM does not suffer from geometric distortions due to generalizations. The DLM 25/1 claims an accuracy of 3m for line shaped objects and points. However, ATKIS provides only the geometry and location of the objects in 2D without any height information. Here the height information is added from a digital terrain map (DTM) which provides the height at ground level and is available in a resolution of 50m for most parts of Germany.

Usually topological relationships are only stored implicitly. The data administration ensures that adjacent objects share the same geometric feature. For instance, the lines of crossroads possess an identical point, and the areas of merging rivers use a common polygon at the border. Only some spatial relationships are represented explicitly, like the knowledge that a bridge passes over a river using the overpass/underpass reference.

The above examples point out that the structure of the digital landscape model mirrors the demands for efficient representation but gives no hints how to control the interpretation. The requirements for automatic interpretation are different and ask for an appropriate landscape model. The landscape model for interpretation was presented in chapter 3.

The GIS software Sicad/open is used for administration of the ATKIS data. A query interface [Pakzad, 97] allows access to the ATKIS data bank during the interpretation. The system can ask for objects with specified properties within the region of interest. Furthermore a description of the object attributes and geometry can be obtained from ATKIS for selected objects.

Figure 3 visualizes the contents of the ATKIS database for the test site Sarstedt.

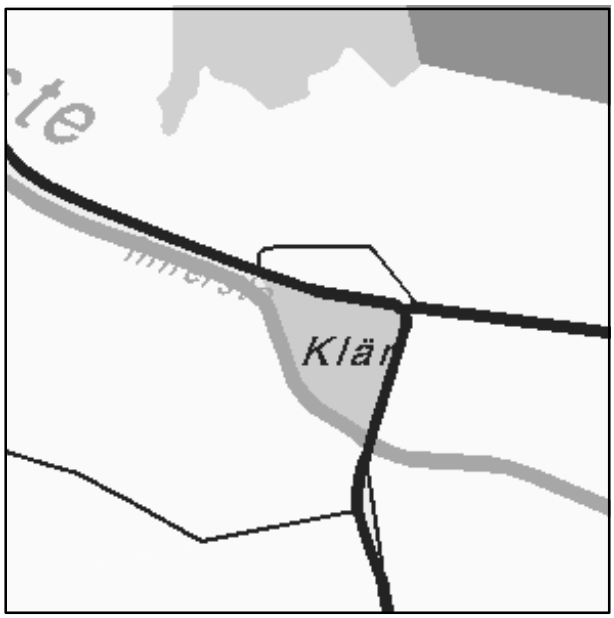

Fig. 3: DLM from ATKIS corresponding aerial image in fig.5

4.2 Scene Description from GIS

The GIS can be viewed as a special sensor that contains symbolic instead of pictorial information. The available scene specific semantic eases the interpretation. Some scene objects, like roads, rivers, etc., have a direct representation in the GIS while others, like crossroads, and river−mouths, do not. The latter objects require a more complex analysis of the GIS data.

The interpretation starts with the generation of a symbolic scene description from the GIS. Figure 4 shows the extraction of a road net from a GIS using the interpretation system AIDA. During the interpretation the state of the instantiated nodes changes from hypothesis I_H to partial instance I_P and finally to complete instance I_C or missing instance I_M. First a seed hypothesis for a $I_{H1}(RoadNet)$ is instantiated. The condition of the rule for complete instantiation is not fulfilled because the obligatory parts are not present. Hence the rule $R_{Hpart-of:INV}$ for top−down propagation of a hypothesis over a *part−of* link in inverse direction is executed, instantiating $I_{H1}(Road)$. The rule is executed repetitively until the initial concept '*GISRoad*' is instantiated, which can be extracted directly from the GIS. On success a complete instance $I_{C1}(GISRoad)$ is generated. Now successively the condition of the rule R_P and R_C for partial and complete instantiation are true resulting in $I_{C1}(Road)$. The *RoadNet* is instantiated partially because the obligatory road is present but the remaining roads within the context of $I_{P1}(RoadNet)$ are not yet detected. Hence the rule for top−down propagation is executed again to search for the next remaining optional road of the road net. This process is repeated till the request to the GIS fails and results in a missing instance $I_{M3}(GISRoad)$. The failure is propagated bottom−up causing $I_{M3}(Road)$. Now all remaining roads in the context of *RoadNet−1* are established. $I_{C1}(RoadNet)$ in instantiated completely. The status *partial instance* blocks the bottom−up instantiation till the interpretation of the road net is completed. So it is not before now

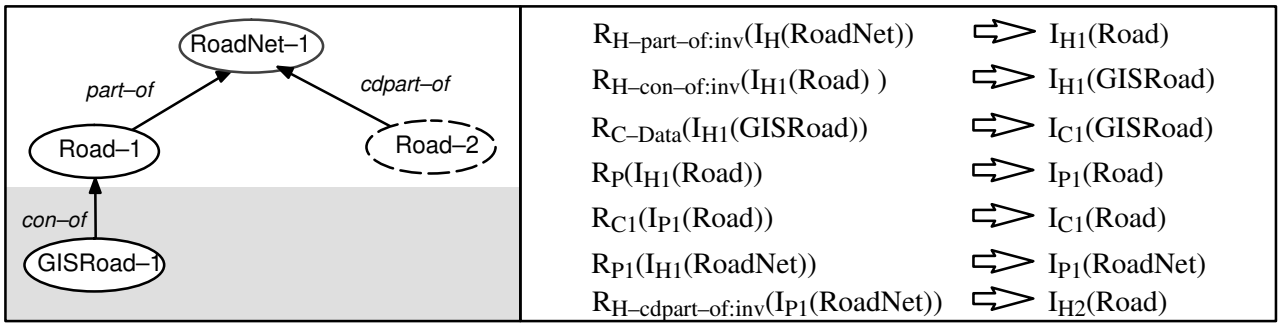

Fig. 4: Scene description and sequence of executed rules with effects on the node status

that the information is propagated to landscape which searches consecutively for remaining parts.

4.3 Integrating GIS in Scene Analysis

The scene description derived from the GIS shall be used as partial interpretation for the analysis of the aerial images. In the first solely GIS based interpretation step the generic model consists only of the scene layer and the GIS layer. The interpretation results in a scene description which contains all objects present in the GIS as complete instances.

In the second step this scene description has to be verified in the aerial images. For this task the generic model is extended by the geometry, material, and sensor layer. In the changed generic model the scene objects have an additional *concrete−of* link to the geometry and material layer. Because this relationship has not yet been verified in the aerial image the link is missing in the scene description. Hence the nodes in the scene layer are reset to the state *hypothesis*. In AIDA control mechanisms ensure consistent interpretation states when the generic model is changed.

In the following chapter the hypothesized scene description from the GIS is used to constrain the interpretation of the aerial images.

5. INTERPRETATION OF AERIAL IMAGE

5.1 Transformations between 3D and 2D Layers

During the analysis of the aerial image constraints have to be propagated from the 3D geometry layer to the 2D sensor layer and vice versa. The 3D to 2D transformations are modelled by sensor specific computation functions.

5.1.1 Projection: The transformation from the 3D world to 2D aerial image is described by a perspective projection.

5.1.2 Reconstruction: The inverse projection from 2D image coordinates to 3D world coordinates is based on a depth map computed by stereo matching with another overlapping aerial image. The resulting disparity for each pixel is transformed into a depth map $\tau(i,j)$. It contains the distance of the observed scene surface from the camera center $\vec{c}$ along the line of sight $\vec{s}(i, j)$ for each pixel. The corrsponding 3D coordinate $\vec{p}$ of an image point (i,j) is given by

$$\vec{p} = \vec{c} + \tau(i, j)\ \vec{s}(i, j) \qquad (1)$$

5.1.3 Extraction of ROI from GIS: To analyze the aerial image the corresponding section of the scene has to be determined. This requires the transformation of the image corner points into world coordinates. The inverse projection is computed from the depth map according to eq. (1). The world coordinates of the corner points define the region of interest to be extracted from the GIS.

5.2 Road Extraction

The roads extracted from the GIS constitute a hypothesis that does not always match exactly with the roads in the aerial image. The hypothesis is propagated top−down generating I_{H1}*(3DStripe)* and I_{H1}*(2DStripe)*. During the propagation from the 3D geometry layer to the sensor layer the geometry attributes are converted. For example the width measured in meter is transformed into pixel. Furthermore the 3D world coordinates are projected into 2D image coordinates.

Before the hypotheses I_{H1}*(2DStripe)* can be tested in the image data the material properties must be constrained. The material is constrained top−down from I_{H1}*(Road)* by I_{H1}*(Asphalt)* and I_{H2}*(2DStripe)*. During the propagation the material specific properties, e.g. reflectivity, roughness are transformed into the sensor specific photometric appearance, e.g. brightness and texture. Here the expected brightness of asphalt in the aerial image is computed.

The two hypotheses I_{H1}*(2DStripe)* and I_{H2}*(2DStripe)* that constrain the geometric and photometric properties respectively are merged because they belong to the same scene object I_{H1}*(Road)*.

Now the hypothesis I_{H2}*(2DStripe)* can be tested in the image data. The expectation about the brightness, width and orientation of the stripe can be used to select an appropriate segmentation algorithm and adapt its parameters. Figure 5b shows the stripes extracted by an algorithm suggested in [Mayer, 96]. The segmented stripes are represented in the semantic net as instances of the concept *ImageSripe*. Due to the segmentation one or more extracted stripes from the aerial image are required for one expected *2DStripe*. To take this into consideration the *2DStripe* in the generic model is composed of several sub stripes. The extraction of the *2DStripe* starts with the search for the first I_{H1}*(SubStripe)* within a search area given by the expectations from the GIS. From the segmented stripes the best match, e.g. the longest within the search area, is selected and linked via *data−of* to I_{C1}*(SubStripe)* which is completely instantiated. Consecutively the next and previous *SubStripes* are searched for. Their expected location is further constrained by a maximum distance and an angle for the difference in orientation.

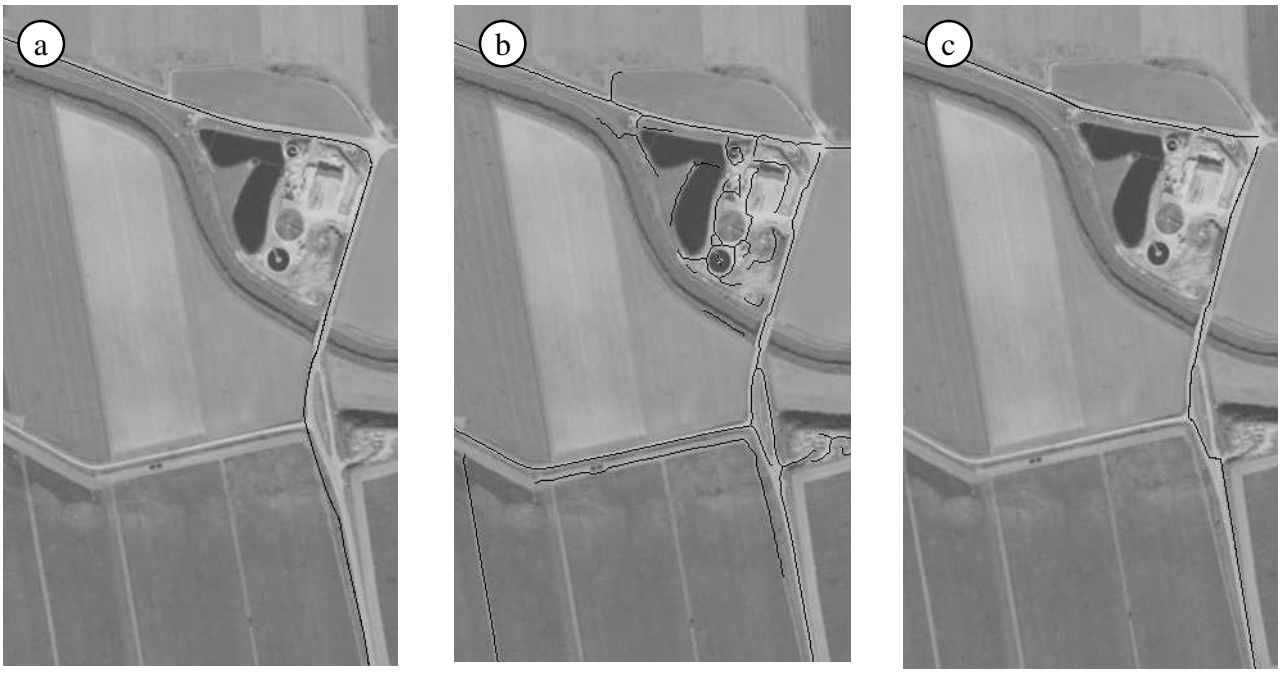

Fig. 5: Aerial image with a) road from GIS, b) segmented stripes, and c) extracted roads with updated location.

The propagation of this topological constraint is modelled by the attributed relation *close−to* with the attributes distance and angle. The *close−to* relation propagates the topological constraint to I_{H2}*(SubStripe)*. When the next *SubStripe* is searched for in top−down direction the topological constraint I_{H2}*(SubStripe)* is merged with the constraints propagated top−down. Again if a stripe primitive in the aerial image matches the expectation I_{C2}*(SubStripe)* is verified. This procedure is repeated till I_H*(SubStripe)* fails and causes I_M*(SubStripe).*

If more than one segmented stripe matches the expectations of I_H*(SubStripe)* the search node, i.e. current interpretation, splits into competing interpretations for each possible segmented stripe. The search nodes are judged and the most promising search node is investigated further.

The extracted *2DStripe* causes the instantiation of a *3DStripe* that models the continuous course of the road in 3D.

5.3 Forest Extraction

The extraction of areal features like forests requires the segmentation of regions. The aerial image is segmented into regions of same texture using a supervised segmentation. The textures are described by Gibbs random fields [Gimmelfarb, 91]. Figure 6a shows the segmentation results. The GIS can be used to define learn regions for teaching the supervised segmentation. Pakzad et. al. [97] showed this for a supervised segmentation based on texture features.

The segmented image regions are represented in the semantic net as instances of the concept *ImageRegion*. For the segmented regions various texture and shape features are computed. The features (e.g. moments, fourier descriptors of contour, elongateness, compactness, principal axis, bounding rectangle, etc.) are used to select regions, circles, and rectangles from the *ImageRegion* instances.

The forests are extracted from the aerial image by searching for forest roofs that ask for corresponding textured regions in the image. Each extracted surface is modelled by an elevated surface in 3D that considers the height step at the forest edge (fig. 6b). The height is estimated from the depth map. Due to the nadir view the forest edge is occluded or compressed in the aerial image. Here the detailed reconstruction dispenses with sensor data and exploits a generic model with synthetic trees [Tönjes, 96].

5.4 Extraction of Complex Objects

The GIS has a limited level of detail. In the DLM 25/1, for instance, buildings and the components of plants are not yet included. It only contains the use of the terrain like residential area, purification plant, or mine. The detection of these objects requires the decomposition into their structural components. After the detection the result could be used to refine the DLM and to increase the represented level of detail.

5.4.1 Purification Plant: A purification plant consists of sedimentation tanks and buildings. Furthermore, it has a road access and is located close to a river to drain off cleaned water. This knowledge is formulated explicitly in the semantic net using *part−of* hierarchies and *attributed−relations* (fig. 2). Thus the complex task of detecting a purification plant is simplified to the detection of objects like buildings and rivers which must have a specified constellation.

The hypothesis for a purification plant and its location is obtained from the GIS. Testing requires the sequential generation of hypotheses for two sedimentation tanks which again initiate a request for water, cylinder, and finally circle. According to its attributes a dark circular shaped region with appropriate size is selected from the segmented image regions and confirms the hypothesis. The size of the circle controls the diameter of the reconstructed cylinder (fig. 6b). Its height is computed from the depth map. Buildings are detected in a similar way (see below).

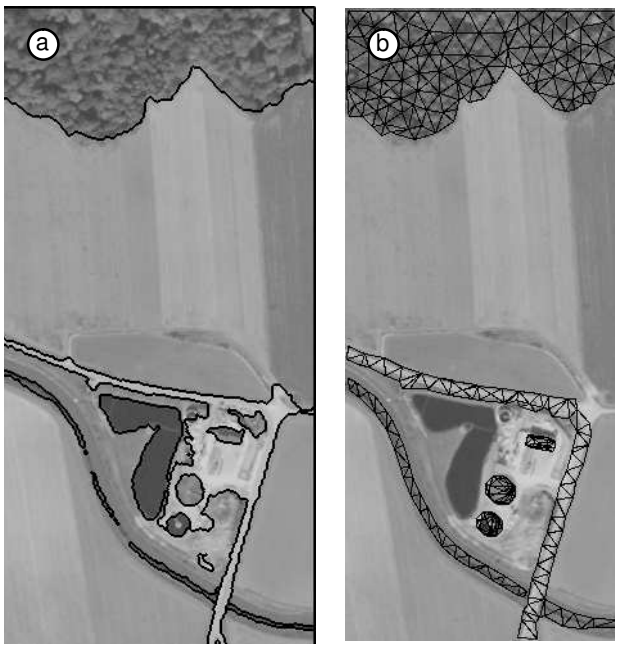

Fig. 6: Aerial image with overlaid a) segmentation results for textured regions and b) extracted forests, roads, rivers, building and sedimentation tanks.

Successively the topological constraints of the *close−to* links are tested. New hypotheses for a close road and river search for these objects in the neighborhood of the purification plant. The purification plant can be instantiated completely if all obligatory components have been found and all required topological constraints are fulfilled.

5.4.2 Buildings: The DLM 25/1 does not contain buildings. However the GIS helps to focus the search on residential areas and the neighborhood of roads.

Buildings can have quite complex shapes and their reconstruction from aerial images is a topic of current research [Brunn, 97]. The presented approach is mainly model driven. The control mechanisms of AIDA are used to constrain successively the size and location of parametric building models. The generic model is shown in figure 2. Buildings are composed of several building wings which are searched for one after the other generating hypotheses for blocks, rectangles, and sub rectangles. The sub rectangles are employed to cope with building wings segmented into several regions which is often caused by different brightness of sloped roofs.

Figure 7 shows a building from the ISPRS test site Glandorf and the segmented image regions. The region is approximated by the hypothesized rectangle and the jutting out parts are newly labeled. The detected rectangle causes the partial instantiation of the 3D block. The initial length, width, and height of the 3D block is computed from the rectangle and the corresponding depth map.

The reconstruction of the 3D parameters from the noisy depth map is inaccurate and results in a coarse 3D model. In contrast to the reconstruction the projection is very accurate. Hence for the fine adjustment of the 3D parameters an analysis by synthesizes approach is employed. The parametric

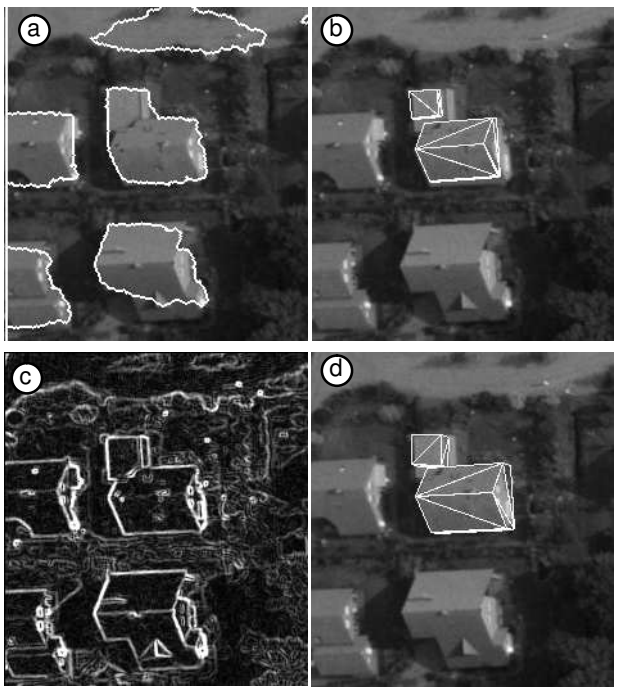

Fig. 7: The initial building model (b) is computed from the segmented region (a) and a depth map. The analysis by synthesizes approach uses the gradient image (c) to adapt the parametric model (d).

model is modified in an iterating manner till its projection matches the image data.

For an accurate match the edges of the 3D model are compared with the grey level edges in the image. For this the hypothesis of edges in the image is propagated top−down and tested in the gradient image (fig 7c). After the parametric model with corresponding edges in the image has been obtained the 3D block is instantiated completely.

When all building wings are established the building is complete. Now specialization starts. It generates a hypothesis for a block with a gabled roof splitting the search tree into a scene description for a block with a flat and a gabled roof. The gabled roof hypothesis is tested in the image data as described above, judged, and compared with the competing interpretation for a flat roof. The most promising interpretation is chosen. Figure 7d shows the resulting building composed of a gabled roof and a flat roofed building wing.

6. RECONSTRUCTION RESULTS

The surface of the extracted objects is approximated by a polygon mesh in space (fig. 6b). The continuous course of the road is modelled by a separate 3D stripe. The forest consists of a surface mesh for the forest roof and an inserted mesh at the forest edge. The parametric models for the sedimentation tank and building are approximated by a polygon for each plane. The aerial image is projected onto the polygon surface and stored in a texture map to synthesize natural looking views of the landscape model. Figure 8 shows a synthesized view of the scene Sarstedt with the reconstructed purification plant in front.

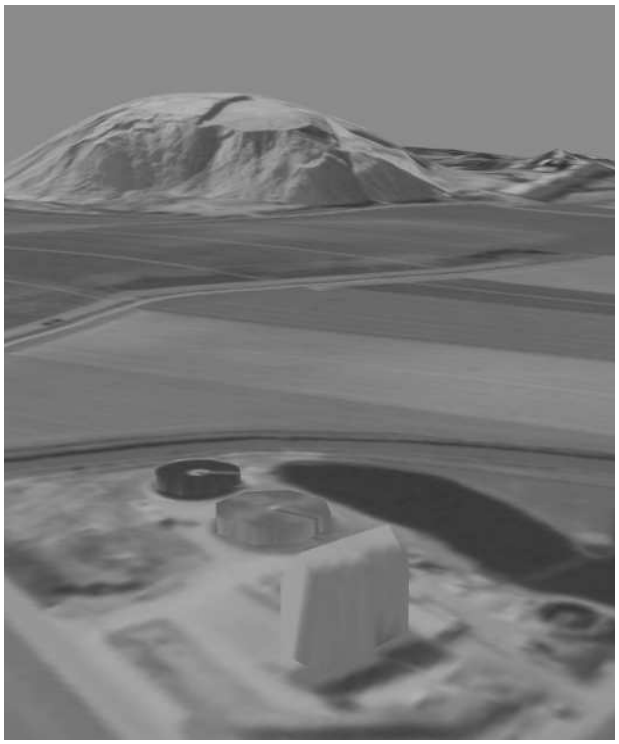

Fig. 8: Sythesized view of reconstructed scene

7. CONCLUSION

A knowledge based approach for the extraction and 3D reconstruction of objects from aerial images was presented. The 3D scene analysis uses general knowledge about the objects and scene specific knowledge from a GIS database. The general knowledge about the structure of the objects and their relationship to the the features in the aerial image and GIS is represented explicitly by a semantic net.

Interpretation exploits the semantic net to derive a symbolic description of the observed scene. First the analysis generates a hypothesis of the objects present in the scene based on a digital landscape model in the GIS. Consecutively the hypothesis is tested in the aerial image.

The GIS supports the interpretaion in three ways. Firstly the objects included in the GIS hypothesize a partial interpretation of the observed scene. Secondly the functional use of complex areal objects, like purification plant or settlement, constrain the expectations about its components and their structure. Interpretation refines the DLM of the GIS. Thirdly the GIS can be used to define learn regions for training a supervised segmentation algorithm. The expectations from the GIS control the low level algorithms.

The scene analysis exploits the interpretation to constrain the parameters of the 3D models used for reconstruction. It ensures that roads run continuously and forest edges shows a height step at the edge, even if occluded. The extracted sedimentation tanks of the purification plant are modelled by cylinders, and buildings by blocks with flat and gabled roof.

The use of general and GIS knowledge provides a promising approach to automate the analyis of remote sensing data.

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