Satellite Image Analysis using Integrated Knowledge Processing

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ABSTRACT

A new approach to satellite image analysis – based on integrated knowledge processing – for improvement of the (up to now often dissatisfying) results and automation of the analysis process will be presented. An expansion of feature base to object-oriented non-spectral features (shape, size, structure, relations) and a systematic structuring of knowledge in semantic networks (SN) are the main components of this concept. Digital topographic databases which are still created in many countries (e.g. ATKIS in Germany) can offer the necessary external knowledge for the semantic modelling of image contents. The analysis is based on a comparison of two specific SN containing knowledge about the topographic data and the image objects, respectifely (generic models 'database' and 'image'). In a first step unchanged objects are verified, while non-verified objects have to be related to their semantic meaning by a general classification procedure. The results of this image analysis will lead in a future step to a change detection and a consecutive update process of the digital database.

KURZFASSUNG

Ein neuer Ansatz zur Satellitenbildanalyse – basierend auf einer integrierten Wissensverarbeitung – soll hier vorgestellt werden, mit dem Ziel der Verbesserung der (bisher oft unbefriedigenden) Auswerteergebnisse einerseits und einer Automatisierung des Auswerteprozesses andererseits. Eine Erweiterung der Merkmalsbasis hin zu objektorientierten nicht-spektralen Merkmalen (Form, Größe, Struktur, Relationen) und die systematische Strukturierung des Wissens in Semantischen Netzen (SN) sind die Hauptkomponenten dieses Konzeptes. Digitale topographische Datensätze, wie sie im Augenblick in vielen Ländern aufgebaut werden, können das notwendige externe Wissen für eine semantische Modellierung des Bildinhaltes liefern. Der Analyseprozeß stützt sich auf den Vergleich zweier spezifischer Semantischer Netze, wobei eines das spezielle Wissen über die topographische Datenbasis, das andere über die Bildobjekte enthält (generisches Modell 'Datenbasis' und 'Bild'). In einem ersten Schritt werden unveränderte Objekte verifiziert, während nicht-verifizierten Objekten ihre semantische Bedeutung in einem allgemeinen Klassifizierungsprozeß zugewiesen wird. Die Ergebnisse der Bildanalyse sollen in einem zukünftigen Schritt zu einer Änderungsdetektion und einem anschließenden Fortführungsprozeß der digitalen topographischen Datenbasis führen.

1 MOTIVATION

Conventional methods for satellite image analysis, such as multispectral classification, to achieve a semantic description of image objects, have undoubtedly reached their limits. This may be caused by the restriction to only one feature, the spectral signature, and the strictly (single-)pixel-based processing without taking the spectral behaviour of neighbouring pixel into account. First approaches were done using local neighbourhood information, for instance by introducing texture or relaxation techniques. But a significant progress can be reached by an expansion of feature base to more then one and the introduction of additional non-spectral object-oriented features.

Beside this improvment of satellite image analysis the automation of the analyzing process should be the second aim of this work. A new approach, which combines both postulations by integrated knowledge processing, will be presented.

2 CONCEPTION

In a first step the spectral feature base is expanded to non-spectral features, which are relevant to improve the satellite image analysis ((VOEGTLE, SCHILLING 1995)). These features will be object-oriented:

spectral features	* signature * texture
non-spectral features	* shape * size * structure * relations

Image objects can differ significantly in shape and size, e.g. rivers, settlement or forest areas. Also different object structures may occur. For instance, urban areas get a specific structure by the street system and the building alignment, which is totally different to the structure of 'natural' objects like forest areas. Relations between objects (e.g. settlement–streets, farm–agricultural areas) can be expressed in rules, which can improve ambiguous classification decisions. However, all this features are more or less fuzzy or uncertain information, so this has to be taken into account during the decision process.

To fulfill the requirements of automation these features should be extracted without interaction of a human operator. Therefore, the representation and integrated processing of external knowledge and general rules in structured form is necessary. Digital topographic databases offer such an external knowledge about the location, size, shape and semantic meaning of objects, which have to be extracted from satellite image information. In many countries – especially Europe and North-America – digital databases in this sense are created or will be finished in the next few years. For example the surveying administration in Germany digitize specific topographic map series and aerial photographs to build up different digital databases, where ATKIS (Amtlich Topographisch-Kartographisches Informationssystem) is the most important one for an integrated processing with satellite image information. The relevant part of ATKIS for image analysis are mainly 3 digital landscape models DLM (= Digitales Landschaftsmodell) related to different scales (1 : 25 000, 1 : 200 000, 1 : 1 000 000). This work is based on DLM200 (1 : 200 000) because the improved image analysis should be used for updating the digital database iteratively. Therefore, the image information should include more details than the database to be updated. A second reason may be the better availability of information in this scale all over the world.

In a first step this work concentrates on areal objects of DLM200, which are main classes of permanent usage, like settlements, forests, water areas and special agricultural areas (meadows, vineyards etc.). For these objects we have a-priori a complete geometrical and semantical description for the whole image area. Therefore, by this symbolic formulated knowledge the integration of a model-driven top-down approach is possible, where in conventional satellite image analysis data-driven bottom-up methods are common.

In contrast to this conventional methods, automated feature extraction and determination of semantic meaning has to take quite new aspects into account. Up to now an human operator chooses interactively only few representative training areas during a supervised classification. This happens by visual interpretation and judgement of the operator based on his/her experience. 'Clean' training areas are chosen, i.e. without disturbance or corruption, e.g. by mixture of classes (parks/lakes inside settlements), geometrical errors (displacements) at the edge of an object or digitizing errors. With DLM200 information all objects inside the image can be used as training areas to extract the actual values of the features out of the image, but the above mentioned disturbances have to be excluded. Therefore, a robust estimation of the features must be carried out. On the base of the extreme large samples an error tolerant method can be created (with the assumption that a majority of the whole concerned pixels in the DLM-objects are valid for the related class).

Because of the object-oriented nature of the above mentioned features the basic concept of this new approach is to build up image segments (by means of DLM-Information), which are candidates for semantic objects. Inside these segments the features have to be determined ('learned') as basic parameters for the decision process (chapter 4) by means of integrated knowledge processing. After this analysis a change detection can be carried out, which leads to an update of the digital database.

3 FEATURE EXTRACTION

3.1 Segmentation

The results of common segmentation methods such as *region growing* or *edge based methods* are not satisfying for inhomogenous areas. Especially settlement areas show a great variability in reflectance values because of numerous mixed classes and mixed pixels, i.e. settlements usually contain also other classes like *meadow*, *forest*, *water* or *agriculture* ((VOEGTLE, SCHILLING 1995)). Therefore, methods were developed which concentrate only to the significant characteristic of the object. With the assumption that this characteristic appears more often inside the concerning object than other ones, a robust segmentation can be achieved by modelling of the interrelations in the image information. So the segment boundaries can differ between image and database information, if the actual status (image) has changed (e.g. increasing of settlement areas, stubed areas in forest etc.).

<u>Example 'Settlement'</u>: Settlements are characterized by a *clustering* of artificial, man-made objects like buildings, streets etc., which contain no vegetation. Because of a (normally) planned development, these objects have specific interrelations (e.g. distances) and build up specific structures. In the image information spatial clusters of pixels with a poor density of vegetation can be found in settlement areas. Because of the great amount of other objects which can appear inside these areas, an enormous inhomogenity in reflectance values is usual. This phenomena (semantic class *settlement* don't coincide with reflectance class) results in dissatisfying segmentations.

As preprocessing step of a new segmentation approach the pixels with a poor density of vegetation are extracted by the method of *Normalized Difference Vegetation Index NDVI*:

$$NDVI = \frac{(IR - R)}{(IR + R)}$$

where IR – reflectance value in near infrared domain
R – reflectance value in visible red domain

With a threshold operation based on a statistical analysis of the NDVI-histogramm the vegetationfree pixels can be marked directly or these pixels are used to build up a spectral signature for a consecutive classification. In both cases we get a more or less spatial clustered class of pixels (fig. 1 and 2, Landsat TM, 26.04.1993). A first approach for modelling neighbourhood characteristic was tried by iterative application of mathematical morphology operators. The basic idesa was to close the (smaller) gaps by *dilation*, afterwards the original size should be achieved by the same amount of *erosion*. Investigations have shown the principle applicability of this method, but if the number of iterations is not high enough, the contourlines and the shape resp. are disturbed (fig. 3). If the number of iterations is too high, the shape gets totally smoothed.

To overcome the problems of morphology operators another approach which is used normally in determination of Digital Terrain Models (DTM), was investigated. Neighbourhood relations can also be modelled by triangulation networks, e.g. Delaunay triangulation, which connects adjacent elements with shortest distances (fig. 4). A statistic of triangle perimeters inside the training areas can be determined. This will be used to select thoses triangles belonging to a spatial cluster. After fusion of valid adjacent triangles we get segments congruent to the spatial clusters (fig. 5).

This method has some important advantages compared with morphology operators: with the distances between adjacent

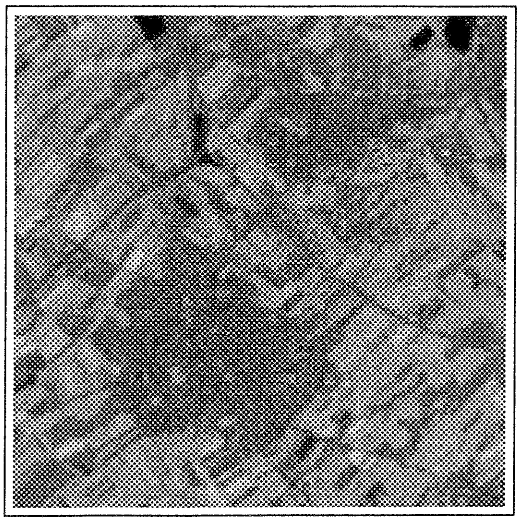

Figure 1: Original test area 'Speyer', Landsat TM, channel 2 (subset of ca. 3km * 3km)

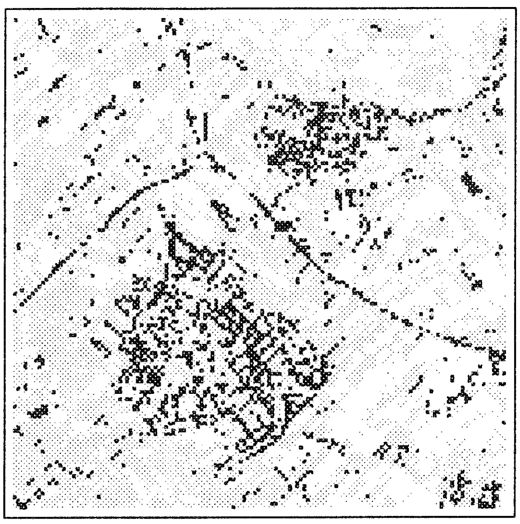

Figure 2: Marked vegetationfree pixels (black) by NDVI (Landsat TM, see fig. 1)

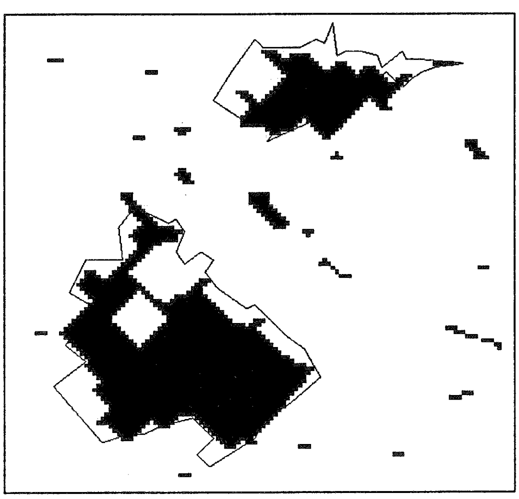

Figure 3: Segmentation of image objects (settlement) by morphology operators (black contour line: original DLM200 objects)

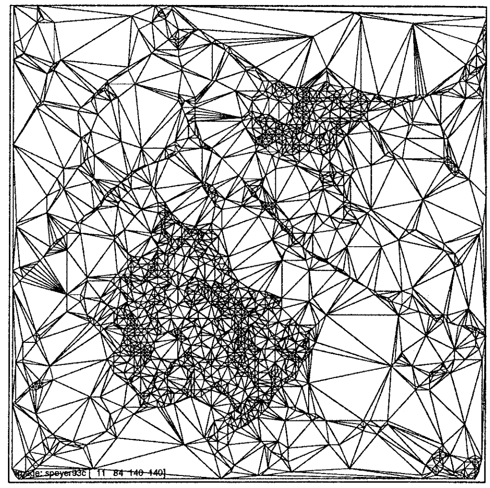

Figure 4: Segmentation of image objects (settlement) by Delaunay triangulation

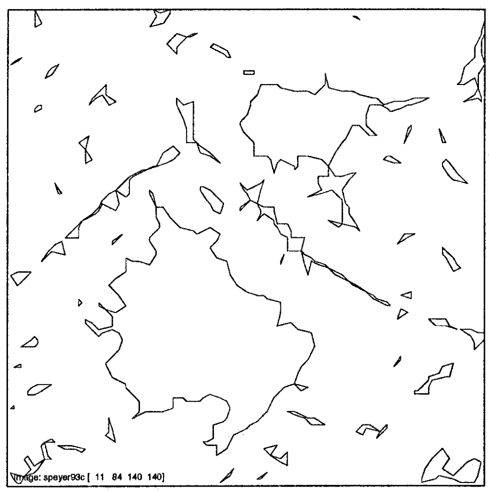

Figure 5: Selection and fusion of valid triangles to segments (settlement)

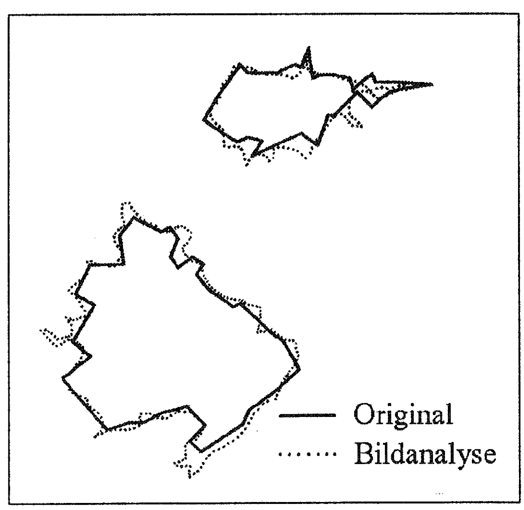

Figure 6: Comparision of shape between original DLM200 objects (settlement) and extracted segments

elements a statistic can be created which can be used later in a decision process to model uncertainty. We achieve a better representation of the object shape (fig. 6) and automatically a raster/vector conversion will be achieved.

Example 'Forest': In a similar way segments of forest areas can be created. The DLM200-objects enable to determine the spectral reflectance values of all forest areas in the image. Assuming that a majority of the captured pixels are valid a histogramm analysis allows to extract the main reflectance behavior, where disturbances, e.g. by stub areas or digitizing errors, are excluded. The related pixels get marked in the same way as 'settlement'. The resulting Delaunay triangulation is shown in fig. 7. After selection and fusion of valid triangles we get the segments for forest areas (fig. 8).

Figure 7: Segmentation of forest areas by Delaunay triangulation (subset of test area 'Speyer')

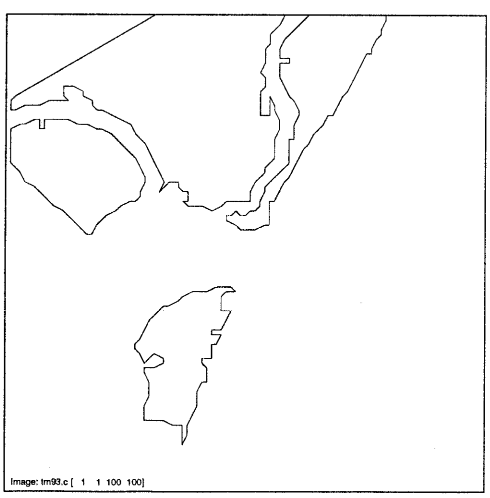

Figure 8: Selection and fusion of valid triangles to segments (forest, see fig. 7)

The other object classes (e.g. *water*) can be treated in analogous way.

3.2 Texture Feature

As mentioned in chapter 2 its necessary to expand the feature base in satellite image analysis, because using only the feature *spectral signature* doesn't deliver satisfying results. The first extention may be *texture* as another spectral – but object-oriented – feature. The investigation of different texture parameters was started with the most common and famous *Haralick parameters* (*homogeneity, mean, entropy, contrast*). Out of these, acceptable (but not optimal) results can be obtained by *homogenity*. Fig. 9 shows the parameter values for different object classes and different training areas.

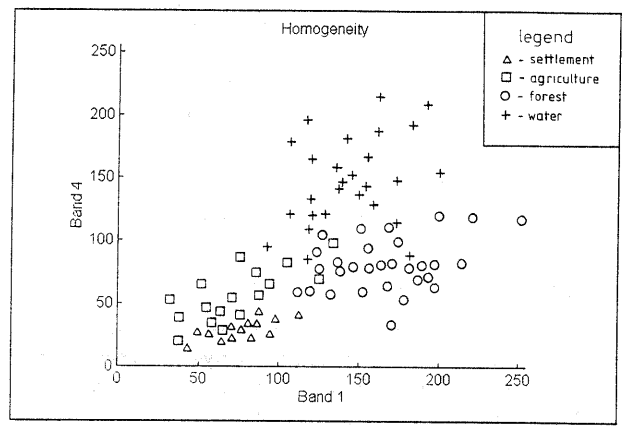

Figure 9: Haralick parameter *homogeneity* as texture parameter for different object classes and different training areas

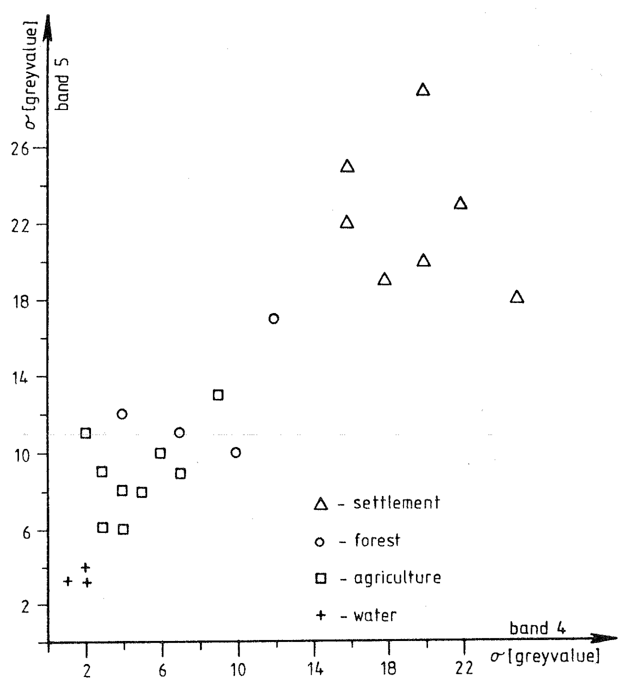

Figure 10: *Modified standard deviation* as texture parameter for different object classes and different training areas

Especially the poor separation between settlement and agriculture areas will produce wrong assignments. As fig. 5 (compared to fig. 1) has shown, there are some confusions caused by harvested or uncovered fields.

A second approach for texture parameter is based on the *modified variance/standard deviation* of the reflectance values inside an object area. Using the common standard deviation disturbances (e.g. by mixing with other classes, digitizing errors etc.) will increase the standard deviation enormously. Therefore, a histogramm analysis of the reflectance values is applied, where the main maximum is extracted. Now the related statistical distribution and its 'cleaned' standard deviation can be determined. The results for the same object classes and training areas (as used for Haralick parameters) are shown in fig. 10.

A better separability can be achieved (compared to the Haralick parameters) – especially between the object classes *settlement* and *agriculture*. This may be caused by the mostly quite inhomogenous texture in satellite images, where the modified standard deviation offers a good robustness.

Markov random fields are just under investigation and deliver (up to now) in the first trials no satisfying results applied to satellite images.

3.3 Shape / Size Feature

Shape and *size* of objects can be used as non-spectral, geometrical features for satellite image analysis. Based on the results of segmentation (where object contours were achieved directly in vector format) parameters for shape and size can be derived.

One of the simplest shape parameters may be 'roundness' defined as area to perimeter ratio. After reducing redundancy in the contour lines, e.g. by *Peuker method*, other more complex parameters like *straightness* or *parallelism* of edges etc. can be determined.

It is very easy to calculate the *size* of an object (or a segment). Using, for instance, the *Gauss* algorithm the size can be computed by means of the image- or absolute coordinates, respectively.

It has to be pointed out again, that both feature contains only *fuzzy* or *uncertain* information in the decision process.

3.4 Relation Feature

Beside the features of the objects itself also the interrelation between the objects carry useful information for image analysis. A part of these relations can be defined in rules, e.g. the relation between buildings and streets, between settlements and agricultural areas. Therefore the relations between all adjacent objects/segments of our working area is modelled explicitely in the decision structure (semantic network).

4 SEMANTIC MODELLING

After creation of segments (incl. their extented features) as candidates for semantic objects, a systematic structuring of the *extracted knowledge* is necessary. This information has to be formalized synthetically. It is used as input for the processing and analysis of image data.

4.1 Analysis System

The first step in semantic modelling of the image contents will be the *verification* of the DLM200 objects in the satellite image by means of the extracted candidates (segments). If objects don't have changed and therefore have (with a certain probability) no significant difference, they can be verified. If not, a general classification procedure is applied to these non-verified objects. To do this methods on higher, symbolic level are necessary. For this special type of data processing general knowledge / rules and specific knowledge about the topographic objects is used. Therefore, the analysis system must be able to represent and process this knowledge. Different formalisms for knowledge representation are known like *predicate logic, rule-based systems, formal gammatics* or *semantic networks (SN)*. SN belong to the most useable schemes concerning knowledge representation. For using and modelling of knowledge about the database (DLM200) and the actual image – as well as central control unit – ERNEST (Erlanger Semantisches Netzwerksystem) is applied in this work ((NIEMANN ET AL. 1990); (KUMMERT ET AL. 1993)).

A SN contains two different types of knowledge: *declarative* and *procedural knowledge*. Declarative knowledge consists of concepts and links, while procedural knowledge contains methods for determination of attributes of concepts as well as for valuation of concepts and relations.

The analysis process is controlled by a special algorithm, which leads to a multi-level analysis concept (fig. 11).

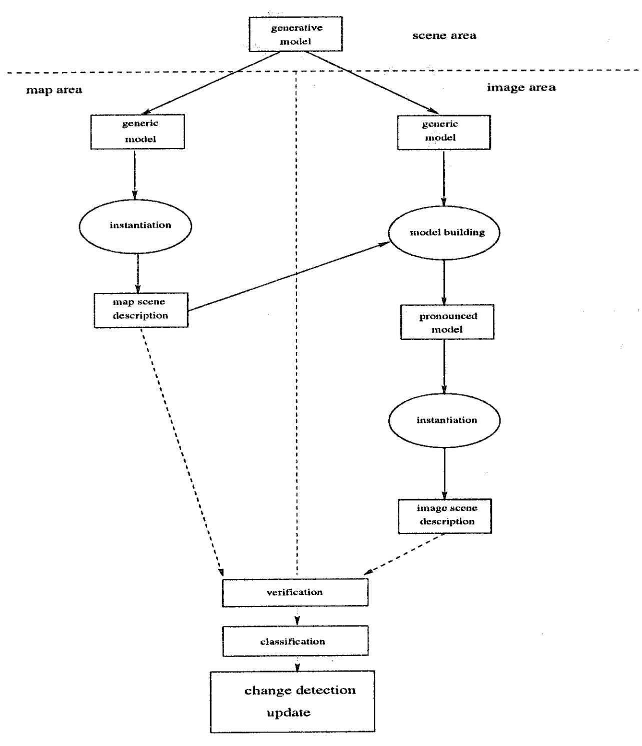

Figure 11: Structure of image analysis

A basic SN contains general knowledge about the scene to be analysed (generative model). In the next step two SN are created containing specific knowledge about the database and about the image objects, respectively (generic models 'database' and 'image'). The analysis is based on a comparison of this two models. In this level procedural knowledge (feature extraction) is added to the knowledge still present. An actual description of the scene in the database domain is built up by means of the generic database model. This description of the 'database scene' will be transformed to the image domain. Combining it with the generic model 'image' automatically a specialized SN for analysis of the scene is created. Now the image analysis based on this model (specialized to the actual scene) is carried out (*instantiation*). A description of the scene in image domain together with the specialized model for the processing of the concerning scene will be the result of image analysis. Verification and classification is not the comparison of two processes executed parallel, but the result of the more error-tolerant analysis procedure (database analysis).

4.2 Data Analysis

The main topic of analysis process will be the verification and classification of image segments (procedural knowledge processing). To achieve the above mentioned structured storage of data the symbolic image information was introduced to a SN. An overview of the SN 'image' is shown in fig. 12, where the different components of the SN can be seen. Beside of this image information – declarative knowledge realized by concepts and links – also the results of feature extraction (additional procedural knowledge) have to be introduced in the SN to enable a successful verification of all image objects based on the 'learned' information.

This analysis is realized inside the SN by creation of suitable valuation- and analysis-functions. The procedural knowledge for analysis of the generic models consists of functions for determination of attributes and parameters of concepts as well as for valuation of the achieved attributes, of the links and the structure relations, where the database (DLM200) acts as an additional information. This functions are different for the database and image domain (resp. for the diverse objects). Therefore, they are determined process-specific.

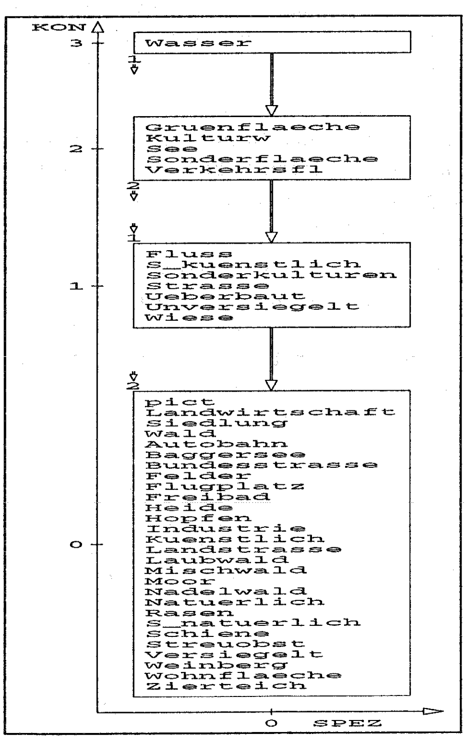

Figure 12: Overview (components) of SN model 'image'

Fig. 13 shows the description graph of the SN 'image'. The connections can be recognized by the the diverse links. On the lowest level the SN is conected to the concrete data, which are stored as segment polygons.

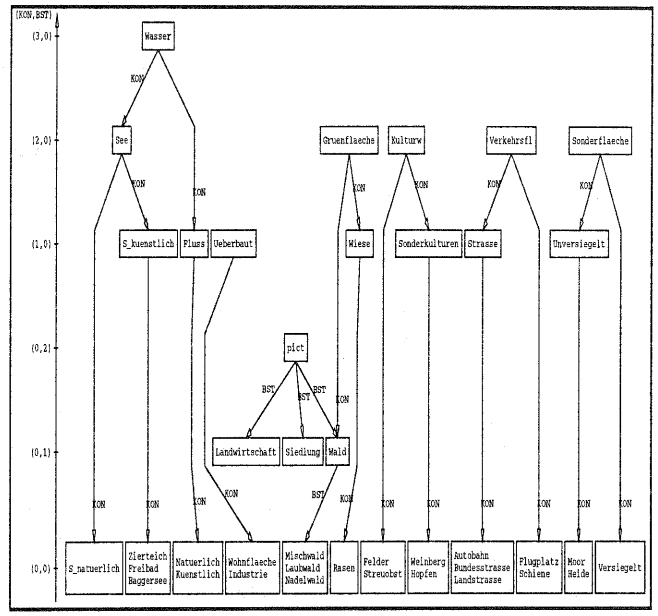

Figure 13: Description graph of SN 'image'

5 CONCLUSION

First experiences with an extented feature base and a special segmentation confirm the efficiency of this concept by achieving a better separability of object classes. The systematic structuring of knowledge in semantic networks is a basic precondition for this integrated Knowledge processing. But the creation of concrete SN has proved to be a very complex and time consuming task. Therefore, specific software has to be developed for automation of this procedure. In the next phase of realizing our concept of semantic modelling the determination of suitable valuation functions in the decision process and the treatment of uncertainty will be the most important aspect.

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