Photogrammetrische Woche 1991
Schriftenreihe, Heft 15, 1991
Institut für Photogrammetrie

Object Extraction from Digital Images

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0 Introduction

Interpreting images is inverting the imaging process using a model of the scene and consists in matching a description of the images with the description of the expected objects' projections and their relations. The classical distinction between object location, reconstruction and recognition results from the simplicity of the objects dealt with or the ability to use human guide within the interpretation process. The generally high complexity of objects or even scenes in Digital Photogrammetry makes the distinction obsolete.

The paper wants to discuss the technical approaches for object location, reconstruction and recognition based on the underlying object models. Section 1 outlines the notion "concept" taken from the area of knowledge representation providing a general framework for modelling also in image interpretation. Sections 2 and 3 provide some examples from object reconstruction and recognition comparing the different techniques used so far. Section 4 finally gives an example for an object model integrating object reconstruction and recognition which may be used in remote sensing for land use mapping.

1 Object Models

1.1 Concepts

We assume that a scene, i. e. a part of the world, can be described by the objects in the scene and their relations in space and time. This implies that a symbolic description of a scene, thus also of an image, is adequate for our task of image interpretation.

For computer supported image analysis we need a suitable representation and a general enough notion about what we mean by "object". We want to use the notion of a concept, as it forms the link to any type of knowledge or model based vision and seems to be used – possibly with modifications – in various existing vision systems (cf. RISEMAN/HANSON 1984, NIEMANN et. al. 1985, McKeown 1987).

According to REIMER (1991) a *representation* contains representation*structures* and *rules* how to map these structures to features of the real world. These rules are the *interpretation* of the representation. The structures may be very simple, e. g. a raster or a list or more complicated, e. g. a set of relations or a semantic net. The interpretation is necessary in order these structures to have a unique meaning, e. g. the number, say x_i, in an list $\{x_i\}$ to mean temperature $x_i{}^o$ C. Of course the choice of the representation is free, i. e. the same set of objects may be represented in different structures. Often it even is meaningful to have multiple representations for the same object in order to be efficient.

We want to distinguish between representation and *description*, a description having a certain representation structure but fixed values, e. g. $x_i = 15$, meaning the temperature 15^o C, thus describing a specific property of an object.

We also want to use the notion of a *concept* to denote a certain piece of knowledge, and thus generalize the term object. According to REIMER a *concept* is a 3-tupel {*concept name, extension, intension*}. The extension contains all objects which belong to the concept. The intension contains all features which an object must have in order to belong to the concept. Thus the intension of the concept immediately gives the means for object recognition. The concept therefore contains a *model* of an object *class.*

Often it is convenient and sufficient to just use the properties of an object for identification. This is common practice in remote sensing where classes are represented by the mean and the covariance of a (spectral) feature vector. The same technique often is used for identifying isolated flat parts on a conveyor belt in industrial applications, using area, circumfence or EULER number as features.

It is obvious that the intension of an object cannot be complete in general, but has to be seen whithin the context of a specific task. In complex scenes the features, an object has to have, may refer to other concepts (via their name), e. g. parts of an object, establishing *semantic* relations, e. g. *part–of, is–a, contains, happens–before* etc., to name a few. The definition of a concept therefore generally leads to recursive structures.

In addition, we may distinguish between class concepts and *individual concepts*, where the extension of the concept contains several or *only one* object resp. Individual concepts thus are equivalent to objects. The recursive structure of the definition makes the distinction between classes and objects context dependent: The concept "tree" in the sentence "Trees are green" may represent the single object "tree" within the class of plants or may represent the class of trees, having palms as subclass. Individual concepts are said to be an *instance–of* a class concept, in case they belong to this class. Together with the above mentioned relationships we are able to build up rich descriptions of a scene, being of the structure of a *semantic net.* How to actually represent the extension and especially the intension of a concept we do not want to discuss here.

1.2 Models for image interpretation

The object models used so far in Digital Photogrammetry now easily can be described within this framework and also cover the imaging process itself. Examples are:

- Object points, image points and projection centres are concepts whose intension are (point-) numbers and coordinates, possibly standard deviations and which are linked by the collinearity relation.

- Digital images may be represented as a matrix. The matrix format on the other hand may be intensionally used to define a digital image, allowing digital elevation models (without break lines) or a covariance matrix to be interpreted as an image. Such images may be concepts for input and output of image processing routines, called by a certain algorithm, thus concepts also may be procedures within a processing chain.

- Relational descriptions inherently link point–type, line–type and area–type concepts both in image processing as well as in digital cartography. Such relational descriptions themselves may be used for object location in case the object model is provided in such a form (cf. GMÜR/BUNKE 1988, VOSSELMAN 1991).

The models discussed so far have in common that the number of features and relations is fixed, either being of continuous type (e. g. length, coordinate) or discrete (e. g. EULER number, predicate *connected*). These models of concepts may be termed *specific* or even *parametric*, in case only continuous features are involved.

Complex objects require *generic* models or concepts where in addition to unknown para or predicates the structure is free to a certain degree. Examples are:

- The generic model of FUA and HANSON (1987) states (the appearance of) a house to homogeneous area in an image bounded by a closed polygon containing only rectangles. T the *number* of the sides remains unspecified.
- A generic model for 3D-houses with flat roofs may be described by general polyhedra with faces having normals only parallel to the three coordinate axes. This "Legoland" model frequently is also used to model the interior of buildings (cf. e. g. STAFORINI et. al. 1990). In this case not only the number of faces is free but also their geometrical relations.

The distinction between specific and parametric models on one hand and generic models on the other hand is essential when developing techniques for object extraction:

1. The location or reconstruction of objects for which parametric models are adequate can be reduced to parameter estimation. We must, however, be aware that the given (image) data are by no means clean, i. e. generally no unique relation between observations and parameters exist. This is due to the unavoidable background noise, image features which do not belong to the object to be extracted. Therefore efficient robust techniques have to be developed and applied. The establishment of parametric models can be based on the broard knowledge of geometry and physics. Thus a large arsenal of techniques is available for dealing with parametric models. The same holds for the recognition task, where in case of specific models Maximum–Likelihood classification can be used to advantage.
2. For objects described by generic models these methods cannot be used at all, except at the very end of the analysis. Already in case of occlusions heuristic search techniques may have to be applied in order to achieve the link between observed features and model variables (observations). Implicitly occlusions transform specific models into generic ones, as the visible parts have to be identified first. Therefore optimization techniques which can handle all types of relations (parametric features, predicates, weak and crisp conditions etc.) and large, generally discrete search spaces have to be used.
3. Besides these technical reasons, the distinction between specific and generic models is made purposive: Nearly all objects we want to extract from aerial or satellite images are of such a complex nature that only generic models are able to adequately represent them. But practically no such model is available today. It is one of the major tasks of photogrammetric research to develop such models in order to start solving the interpretation problem.

An example for such a model is given in section 4.

2 Object Location and Reconstruction

Object location and reconstruction deal with individual concepts and aim at instanciating, i. e. determining the parameters of a specific object namely datum and/or form parameters resp. The following examples – sorted according to increasing complexity of the models – want to representatively demonstrate the different estimation techniques. Special emphasis is layed upon the description what type of model for the background (non-object) is assumed and how object and background are separated, in case this is necessary.

- Classical area based image matching, using cross correlation or least squares matching, refers to a low level representation and to a global or local (gradient) search for determining the parallaxes. The object is fully described by the given intensity array. This explains the difficulty such low level techniques have with illumination changes or varying background. A typical – up to now nonsolved – problem is the low level and therefore (!) high precision location of targeted points in aerial images, especially targeted control points, which is due to the unability to reliably model the varying background.
- The surface reconstruction method proposed by HELAVA (1988), EBNER et. al. (1987) and WROBEL (1987) aims at detemining the fixed number of grid heights of a digital elevation model and the also fixed number of the reflectance parameters of the unknown surface using classical least squares. It is a closed model which allows all types of generalizations as long as no occlusions occur. Again, in case of occluding contours these are part of a generic model, as their number and structure is not known. The approach of the MATCH-T–Program (KRZYSTEK 1991) at least is able to deal with local disturbancies (trees etc.) via a robust estimation. Such a robust estimation can be interpreted as a parametric tool to determine the – in principle unknown – number of outliers (cf. BLAKE/ZISSERMANN 1987). In case breaklines explicitely are to be determined a generic model, going with a more complex data structure, has to be established.
- The control point location technique used in the program AMOR (cf. SCHICKLER 1991, SESTER/FÖRSTNER 1989) contains a parametric model for the orientation of the image and the form of the control points. The model is represented by a list of straight line segments. A clustering algorithm is used to cope with the background noise and robust estimation techniques are applied to handle matching errors.
- The location of three dimensional objects of a given structure needs to explicietely take occlusions into account in case no or poor approximate values are available. In this case the pose determination has to be preceeded by a heuristic search for the correct correspondencies, which is due to the perspective projection and the unknown lighting conditions. It has to rely on a relational description including low–level features (points, lines and areas) and their mutual, mainly topological, relations. Heuristic search techniques therefore can be seen to be the most robust techniques for paramter estimation – of course also the most costly ones, because of the exponential algorithmic complexitiy. The identification of the correct correspondencies may on the other hand be interpreted as feature recognition, as the search process consists of a sequence of doing and undoing decisions. Therefore more powerful evaluation techniques than the average sum of the squared residuals have to be applied (cf. VOSSELMAN 1991).

The examples are representative with respect to the model types and the estimation techniques used. This indicates that already for objects, described by specific models, e. g. a relational description, classical estimation techniques and the corresponding evaluation techniques are no longer applicable, but techniques to deal with large discrete search spaces together with more general optimization criteria have to be used.
This directly forms the link to the methods applied in object recognition.

3 Object Recognition

Object or pattern recognition aims at instanciating, i. e. determining the class of a given object. Here the above mentioned intension of a concept is used explicitely. In most cases a set of concepts, i. e. classes is given from which the unknown object may be taken.

The intension of the concept may be given by the designer of a system, but in many cases has to be learned from training sets, i. e. extensions of the different concepts. The criterion then is to find decisive features, which enable to distinguish between the different classes.

There is a vast amount of literature on statistical pattern recognition (e. g. FUKUNAGA 1972, TOU/GONZALEZ 1974), dealing with objects which adequately may be represented by (stochastic) feature vectores, i. e. lists of attribute value pairs describing their properties. Structural pattern recognition (e. g. FU 1982) resulted from the unability of adequately representing complex patterns , e. g. road networks, buildings or hand written letters using feature vectors alone.

Whereas statistical pattern recognition relies on multivariate distributions, often reduced to GAUSSIAN, being the basis for the current implementation of most multispectral classification schemes, structural pattern recognition provides a rich arsenal of tools to describe and identify complex patterns. In practice both methods are used in intimate combination (e. g. FU 1982, NIEMANN 1989).

In statistical pattern recognition BAYES' rule plays the central role:

$$P(\omega \mid \mathbf{x}) = \frac{P(\mathbf{x} \mid \omega) P(\omega)}{P(\mathbf{x})} \tag{1}$$

as it allows to combine a priori knowledge probability $P(\omega)$ about the occurance of class ω and the uncertainty $P(\mathbf{x} \mid \omega)$ of the obseved features $\mathbf{x}$ for a given class to determine the likelihood of the class ω occuring in presence of the observed values $\mathbf{x}$. For $P(\mathbf{x})$ being constant and generally unknown, maximizing (1) over all classes ω_i is the same as choosing the class ω_i where the probability

$$P(\mathbf{x}, \omega_i) \rightarrow max \tag{2}$$

of the class ω_i and the given data $\mathbf{x}$ occuring simultaneously is maximum. This reveals two important consequences:

1. In case of feature vectors $\mathbf{x} = (x_j)$ containing (independent) *discrete* and *continuous* variables, BAYES' rule can still be applied. E. g. for two variables x_1 being continuous, x_2 being discrete, $P(x_1, x_2, \omega_i) = P(x_1, \omega_i) P(x_2, \omega_i) = p(x_1, \omega_i)\, dx_1 P(x_2, \omega_i)$ can be maximized with respect to ω_i where $p(x_1, \omega_i) = p(x_1 \mid \omega_i) P(\omega_i)$ is the density function of (x_1, ω_i), showing that the choice of the size of dx_1 does not influence the decision. This e. g. allows to mix geometric parameters and relations within the classification.

2. In case the classes ω_i represent more complex objects, ω_i may be split into two parts $\omega_i = (\mathbf{p}_i, m_i)$ where m_i is the class type and $\mathbf{p}_i$ the parameter vector describing the class more in detail. The size of $\mathbf{p}_i$ may depend on the class. Then BAYES' rule still can be applied. FUA and HANSON (1989) e. g. use a generic model for man made objects (cf. above) where m_i may be related to the number of polygon sides circumscribing the object, and $\mathbf{p}_i$ to the parameters describing the polygon in detail. Then maximizing

$$P(\mathbf{x}, \mathbf{p}_i, m_i) \rightarrow max. \tag{3}$$

consists of choosing the most likely description of the intensity data $\mathbf{x}$, the geometry $\mathbf{p}_i$ and the polygon type m_i.

Taking negative logarithms (base 2) and rewriting leads to

$$I(\mathbf{x}, \mathbf{p}_i, m_i) = I(\mathbf{x} \mid \mathbf{p}_i, m_i) + I(\mathbf{p}_i \mid m_i) + I(m_i) \rightarrow min. \tag{4}$$

representing the *minimum description length principle.* The three terms on the right side can easily be determined by experiment or by using a model. Moreover, as $I(x)$ can be interpreted to be the number of bits to describe x, no probability needs to be associated with x explicitely (cf. RISSANEN 1989).

Therefore a close link can be formed between statistical and structural pattern recognition techniques, as far as the evaluation is concerned.

The actual classification procedures, however, essentially use search techniques, whatever optimization function is used:

- Using BAYES' rule (1) or (2) to identify the optimal class corresponds to complete search.
- In case the number of classes is large hierachical schemes are frequently applied leading to decision trees which reduce the effort for determining the probabilities. The setup of such trees within the learning/training phase may use various clustering algorithms, which aim at a high separability whithin the first levels of the decision tree, assuming that superclasses are more easily to be distinguished than the final classes. In object recognition decision trees often are based on view classes, such view classes representing sections of the parameter space where certain features of the silhouettes or the visible faces have common or similar properties (cf. e. g. IKEUCHI 1987, LIU/TSAI 1990).
- Identifying complex objects which only can be described by generic models is the main issue of image understanding research. No commonly accepted overall approach is available. Though heuristic search techniques, especially the A^*-Algorithm with its modifications, are widely used as a search tool, the problem is the still too large search space which enforces stepwise procedures, namely based on grouping image features and pieces of derived knowledge about the scene using sophisticated control structures.

  Probably the most advanced system for extracting buildings from stereo images has been developed by D. MCKEOWN and his group (cf. SHUFELT/MCKEOWN 1990). Their approach is based on the assumption that no single algorithm is able to extract buildings reliably, but several methods have to be combined in a cooperative manner. They link procedures for extracting buildings based on line-corners and shadows whose results are then grouped to set up hypothesis for buildings. The quantitative check against ground truth reveils errors on an average less than 0.1 to 0.2 mm at an image scale of approx. 1 : 13 000. The system combines recognition techniques, e. g. for evaluating rectangles between neighbouring line segments, and reconstruction techniques for deriving 3D-coordinates in an intimate manner. An evaluation of the overall performance of the system however has to rely on such tests, as no formalization of the implemented strategy is available.

4 Modelling Land Use Maps for Remote Sensing

This section describes an ongoing effort to recover land use maps from remotely sensed data. The object model integrates the multispectral and multitemporal data and the parcel structures in order to be able to jointly evaluate reflectance and geometry data in image interpretation. The object model is presented and the key problems to be solved are discussed.

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Fig. 1 shows the assumed relation between map, topography and image

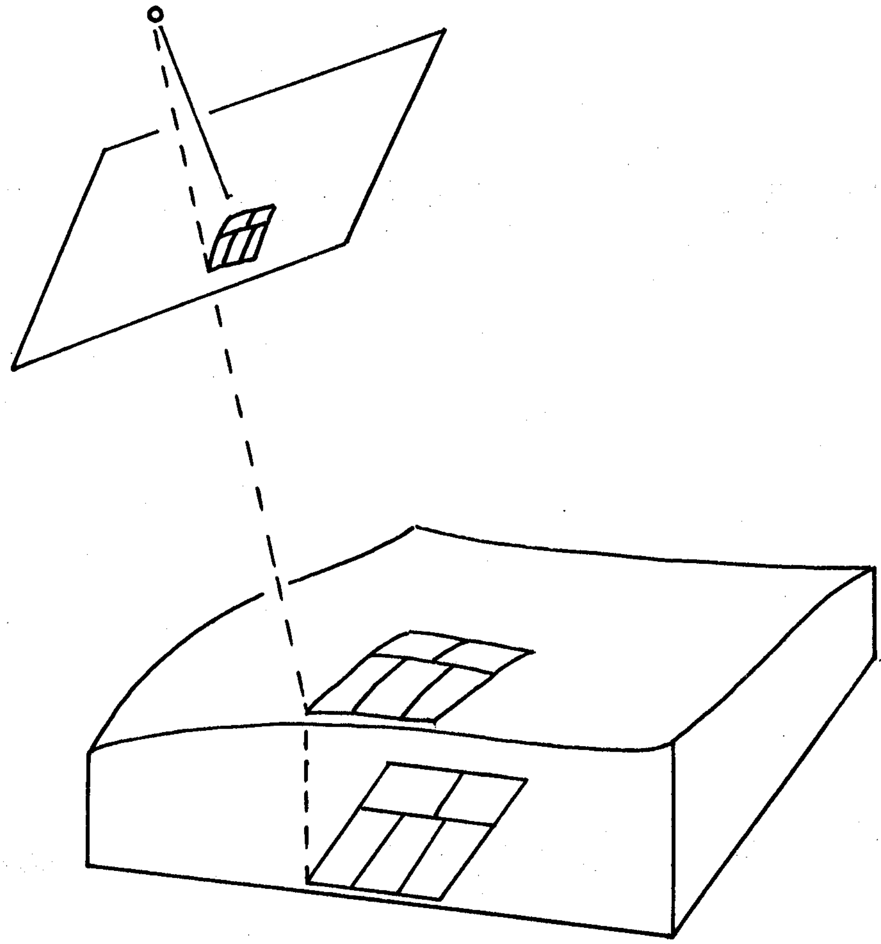
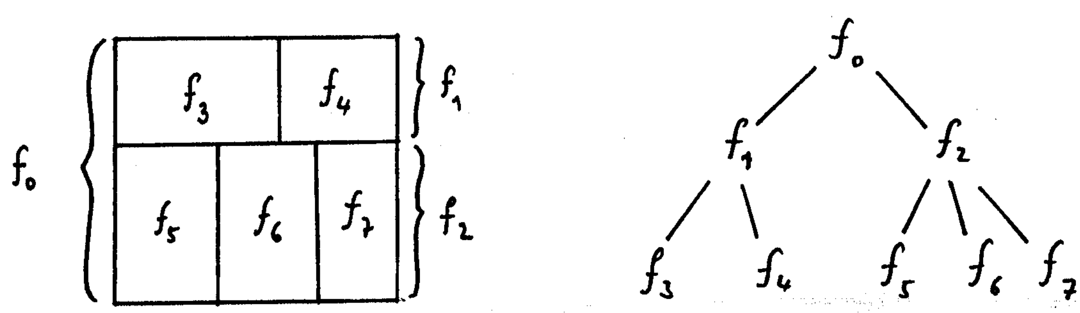


Fig. 2 shows an example for the recursive partitioning of an area and its generation tree



4.1 The object model

The aim is to build a land use map from several digital images, either digitized aerial photographs or scanner imagery.

The model consist of several parts (cf. Fig. 1):

- A map.

  It is assumed to be a planar graph of a certain structure where each area belongs to a class.

- A model for the structure of the graph.

  The structure of the planar graph generally shows regularities, which may be modelled using a stochastic tree grammar (cf. FU 1982) describing the recursive partitioning of larger parcels into smaller ones during reallotment. The reason for this type of generic model is its natural representation and the possibility to derive the probability $P(\omega_i)$ of a segmentation ω_i, which itself has a complex structure. This probability can be combined with the conditional probability $P(\mathbf{x} \mid \omega_i)$ derived from the homogeneity of the regions defined by this segmentation according to (FUA/HANSON 1987). The geometric model of the land use map therefore is a generalization of their model. The selection of the best interpretation, based on intensity, colour or texture and geometry, thus is based on the minimum discription length principle.

- A model for the dependencies of the reflectance properties on time, in case this is available and necessary.

- A digital elevation model.

  Together with the above mentioned model parts it forms a generic model of the topography.

- Images of the scene.

  They generally will be multispectral, multitemporal and reveal different pixel sizes.

The model is a generalization of the one by HELAVA (1988), EBNER et. al. (1987) and WROBEL (1987) with respect to modelling the surface into homogeneous regions.

Fig. 2 shows an example for the recursive partitioning of a large parcel into smaller ones representable by a generation tree, starting from area f_0, partitioned into f_1 and f_2, and then into 2 and 3 smaller areas. The way how a node in the tree is splitted is assumed to be independent on a.) the parent node and b.) on the cousin nodes within the same level. It will however depend on the form, the area, possibly orientation or other properties of the partitioned parcel. The probability distribution of the number of child nodes and their geometric properties has to be learned from real data.

The probability in this special case can be written as

$$
\begin{aligned}
P(\omega_i) &= P(f_0, f_1, f_2, f_3, f_4, f_5, f_6, f_7) && (5)\\
&= P(f_3, f_4, f_5, f_6, f_7 \mid f_0, f_1, f_2) P(f_0, f_1, f_2) && (6)\\
&= P(f_3, f_4 \mid f_0, f_1, f_2) P(f_5, f_6, f_7 \mid f_0, f_1, f_2) P(f_1, f_2 \mid f_0) P(f_0) && (7)\\
&= P(f_3, f_4 \mid f_1) P(f_5, f_6, f_7 \mid f_2) P(f_1, f_2 \mid f_0) P(f_0). && (8)
\end{aligned}
$$

In case the forms f_i can be split into the geometries g_i common to all child nodes of the same parent node and their individual deviations d_i, thus $f_i = (g_i, d_i)$ and assuming that the geometry

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of the region splittet into n parts is describable by the $n-1$ first boundaries in the lists we can split the conditional probabilities further, e. g.

$$\begin{aligned} P(f_5, f_6, f_7 \mid f_2) &= P(g_5, d_5, g_6, d_6 \mid f_2) & (9) \\ &= P(d_5, d_6 \mid g_5, g_6, f_2) P(g_5, g_6 \mid f_2) & (10) \\ &= P(d_5 \mid g_5) P(d_6 \mid g_6) P(g_5, g_6 \mid f_2). & (11) \end{aligned}$$

We assumed that only the local geometry, say g_5, e. g. the length of a side, influences the deviations, say d_5. The first two terms describe the probabilities of the individual deviations, e. g. from parallelity, and the last term describes the probability of a certain regular decomposition of the area f_2 with the geometric boundaries of g_5 and g_6, e. g. depending on the side lengths.

The example demonstrates, that under certain independence conditions the probability of the segmentation can be split into the product of easily calculatable conditional probabilities.

The probability $P(\omega_i)$ finally may be used to decide between two segmentations ω_i and ω_j, say, based on the total probabilities $P(\mathbf{x} \mid \omega_i)P(\omega_i)$ and $P(\mathbf{x} \mid \omega_j)P(\omega_j)$ where the first factors are to be derived from the homogeneities of the image data in the segments.

4.2 Steps toward building the map

The reconstruction of the map requires several steps, which have to be worked out in detail:

- As the evaluation of the final interpretation highly depends on the probability of the geometry of the segmentation the grammar of natural partitionings has to be learned from real data. This especially covers the statistics of the numbers of divisions, of the geometry, the dependencies on certain features as well as the check of the independence assumptions. Here statistical and structural learning techniques are applied to map data.

- An initial segmentation based on intensity, colour or texture gradients leads to a polygon network which generally will have also non–closed loops. The process is purely data driven and requires no knowledge about the scene, thus works without user specified thresholds (cf. WEIDNER 1991).

- Grouping the line segments into rectangular, rhomboid or other low order closed polygons uses proximaty and continuity conditions and model knowledge about the likelihood of parallel lines, number of polygon sides etc. Conflicting hypothesis or complex nodes may be resolved using the minimum description length principle. The result will be a set of – generally still conflicting – hypothesis about homogeneous areas.

  A second grouping process can be used to find sets of parcels of common orientation which will reduce the number of hypothesis used in the final interpretation step. An example of successful grouping in a hierachical manner is given by MOHAN and NEVATIA (1987).

  The final step has to use the assumed structure (grammar) and select the most likely interpretation, based on the probability of the segmentation and the homogeneity within the parcels of that segmentation. In all cases stochastic optimization and/or heuristic search techniques have to be applied.

In case several images are available the information will be joined in object space using the vector representation of the map. This may include the determination of a digital elevation model, if it is not available. The vector representation of the map in object space has severe advantages:

- The classification of the areas refers to land use units not to pixels. Thus resampling of the images can be avoided. On the contrary, each pixel can contribute to those areas where it gets its spectral information from. This solves the problem with mixed pixels. It also significantly increases the quality of the classification (cf. JANSSEN/MIDDELKOOP 1991).

- Images taken at different times serve finding the real boundaries which can be assumed to be stable within one growth period. A growth model may be derived or used to increase the reliability of the classification. Temporal knowledge about sequences of land use may be used (cf. JANSSEN/MIDDELKOOP 1991).

- Information about the legal boundaries of the parcels may, if available, be used as an approximation for the land use boundaries. In this case only small modifications of the initial segmentation are required, namely splitting inhomogeneous segments and merging segments with the same class. In case of satellite imagery with negligible texture within the parcels the estimation of the geometry and reflectance properties can be made simultaneously with the classification using the given image data as original observations.

The limitations of the model are to be found in areas where the third dimension plays a decisive role due to occlusions. The value of the structural model also depends on how regular the field structures really are.

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Abstract: The paper discusses the modelling of objects for image analysis and their use in object location reconstruction and recognition. A concept for land use mapping is presented which is based on a joint model for image data and field structures.

OBJEKTERKENNUNG IN DIGITALEN BILDERN

Zusammenfassung: Der Beitrag diskutiert die Modellbildung, die für die automatische Interpretation von Luftbild- und Fernerkundungsdaten erfoderlich ist, und wie sie bei der Lokalisierung, Rekonstruktion und Erkennung von Objekten verwendet wird. Es wird ein Konzept für die Landnutzungskartierung vorgestellt, das eine gemeinsame Modellierung von Bilddaten und Feldstrukturen enthält.

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