ACQUISITION OF RULES FOR THE TRANSITION BETWEEN MULTIPLE REPRESENTATIONS IN A GIS

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ABSTRACT:

Multiple or multi-scale representation is an issue of growing interest and importance in GIS. It deals with the representation of different spatial entities that describe the same physical objects in one common information system. The need for such a representation - instead of a description of objects on the most detailed level of resolution - results from various reasons. The main reason being the fact that spatial phenomena usually only occur on a certain scale - which is not necessarily the most detailed one. Changes in scale lead not only to changes in geometry, but also in topology and semantic. Multiple representations also result from different interpretations of the given reality according to scale or thematic emphasis, and also due to the date of capture. Since geographical phenomena have multiscale aspects, they should also be represented as such - and not only at one level. This then allows for an inspection of spatial data on various levels of detail - logically zooming in and out. Multiple representation affects data modelling and data capture, integration, storage, analysis and presentation, i.e. all parts of a GIS. Whereas multiple representation first was considered to be a mere cartographic problem, it is getting more and more obvious that it is an important issue in GIS as well.

The paper first introduces into the problem of multiple representation and tries to clarify the terms used. The main emphasis is put on possible realizations of such a representation. This presumes to have a means to generate different levels of detail and provide links between these representations. The paper finally presents a concept for the transition between different scales based on an object-oriented representation. In order to go from one scale to the next, certain rules are required. These rules are partly given a priori, partly they are acquired automatically from given data sets with techniques from Machine Learning. The concept is a extension of a program developed for the derivation of object models for map and image interpretation.

1 INTRODUCTION AND OVERVIEW

Geographic phenomena are highly scale dependent. This fact is obvious in our everyday life, consider e.g. our intrinsic rules of stepping back to get an overview of a given scene, and getting closer in order to distinguish details. Each phenomenon has its corresponding level, where it is best understood: e.g. a sentence cannot be understood on the level of letters. Even individual sentences need the higher order structuring of sections, captions and a table of contents. Such a hierarchical multi-scale representation is used to guide the paths of perception - from coarse to fine. The same holds for information represented in a data base. Usually the information is captured for a certain purpose - which often determines the data model. Thus e.g. in order to investigate *Waldsterben*, individual trees have to be modelled and captured, for landuse classification on a general level however there is no need to identify a single tree, but the forest area as a whole is described.

The perception of our surrounding varies with scale. Both type and appearance of objects differ when getting closer or going away, resp. A given phenomenon thus is not fixed, but scale dependent. Dealing with this fact is an issue in cartography ever since: the national mapping agencies store multiple scale versions of data. It is only recently that there is a consensus in GIS research community that apart from graphics-oriented generalization there is a need for model generalization in a database. Thus also in spatial databases generalization operations have to be applied in order to result in a higher level view of the same phenomena. In this way the understanding and applicability of the data is improved.

1.1 Implications and Related Topics

The problem of multiple representation is straightforward and well known in the domain of cartographic generalization. Multiscale representation has however many other aspects, just to name a few (see also e.g. [Weibel 1995]):

- ▷ Multiscale representation allows for a controlled data reduction concerning spatial, semantic and/or time dimension. In this way data abstraction leads to a reduction of spatial and semantic resolution and to data bases at multiple levels of accuracy and resolution. This in turn has the effect of a reduction of storage space and also of a speed-up of calculations.

- ▷ Going up in the hierarchy, a reduction of unnecessary details and at the same time an emphasis of the important ones is achieved. The different levels of detail may reveal essential information for different users.

- ▷ A severe problem in GIS is the fusion of data originating from different sources. Data can be captured based on different data models and also with different data quality. The data sets are similar in the sense that they are captured at approximately the same scale. In the context of the so-called conflation [Walter & Fritsch 1995] map matching techniques are applied to determine corresponding parts between the data. These methods also have to allow for partial matches. This problem especially occurs when thematic data has to be integrated into general topographic data sets.

- ▷ In image analysis multiscale representation is also an important issue. In order to get approximate values for interpretation or matching, usually coarse-to-fine-approaches are selected, using image pyramids (e.g. [Hahn 1989]) but also a series of symbolic descriptions ([Bobick & Bolles 1989]).

In GIS the following multiple representation problems can be distinguished, which are visualized with topographic data of Germany:

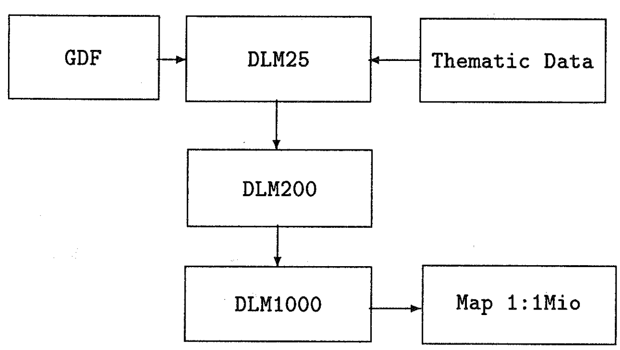

Figure 1: Examples for multiple representation problems, visualized with topographic data available in Germany: ATKIS DLM's (Autoritative Topographic-Cartographic Information System) at three different resolutions, GDF (Geographic Data File: standardized data exchange format in Europe for road traffic data).

model generalization: a bottom-up aggregation (generalization) of objects going from one scale to the next (e.g. transition from DLM25 to DLM200 (Digital Landscape Model 1:25 000 and 1:200 000, resp.)),

cartographic generalization: generalization going from a data base representation to a graphical representation (e.g. cartographic presentation of contents of DLM1000 in a map of scale 1:1Mio),

conflation: matching of data sets of different origin, but describing the same physical reality (e.g. fusion of GDF road data and ATKIS road information).

Whereas the cartographic generalization can be considered as a problem of high complexity (especially the problem of displacement), solutions for the model generalization seem to be closer at hand. The question even rises, if cartographic generalization will ever be achieved - or if it should rely on semi-automatic processes (e.g. with commercial products like MapGeneralizer from Intergraph). Thus the proposed approach refers to the model generalization only.

The term generalization is normally used for cartographic generalization. There it implicates, that the generalized version of an object completely replaces the original one, since it is no longer needed after visualization. Data abstraction or model generalization however results in a a hierarchy of objects - where all manifestations exist side by side with equal rights. In the sequel generalization will however be used to describe both types of data abstraction.

1.2 Possible Realizations

A spatial database comprising multiple levels of detail can be organized in various ways. It can be realized by having a single most detailed representation in conjunction with tools to derive a series of other layers of different scales. The other possibility is to keep multiple representations of the objects on different pre-given levels of detail in the system. The advantage of the first alternative is that only one data set has to be stored, which can be managed and accessed consistently. In the second case redundant data has to be dealt with. On the other hand the time for the calculation of data at a certain scale has to be taken into account. Also - to date - no efficient generalization algorithms are available. Furthermore there is no tool to propagate updates through a series of derived data sets - which is an important issue for database revision.

Ideally a GIS should comprise all possible information - every application then should be able to deduce the problem specific information from it. This presumes to have rules for the transition of representations of objects between different levels of detail. Another still unsolved problem is the selection of the optimal scale for a given task. Thus the following questions arise:

- ▷ Which objects have to be represented in a certain level ?
- ▷ How are these objects represented (point, symbol, line, area, ...) ?
- ▷ When do the objects disappear and how ?

In general, the national mapping agencies have already answered the first question. E.g. the surveying authorities in Germany have detailed descriptions of the objects to be represented in a map of a certain scale (ATKIS ([Harbeck 1995]) - a general framework for a digital representation of the map data). These descriptions, so-called object catalogues, also include the way the objects should be captured, their accuracy and representation in terms of geometric primitives (point, line, polygon). They are however only given for certain discrete scales (scales 1:25 000, 1:200 000, 1:1 Mio). In order to generalize to other intermediate scales, such catalogues have to be established accordingly. There is a great demand for intermediate representations: especially for environmental planning a scale 1:50 000 is very favourable ([Winkelhausen 1995]).

Even when the representation of the objects on distinct levels is given, the question arising immediately is how to define the transitions from one scale to the next. For small changes in scale smoothing operation can be applied (cf. processes in digital image processing: gaussian smoothing ([Sester 1990]) or morphological operations). At a certain level however, there are abrupt changes in the representation which cannot be reflected by elementary processes, but have to be represented by a set of rules (e.g. transition from geometric to symbolic representation).

1.3 Sketch of proposed approach

The idea of this contribution is to use an object oriented representation in conjunction with techniques from Machine Learning. The elementary representation of the objects of the catalogue is straightforward. The object-class hierarchy can be transferred directly. Each object has a set of methods, which define its behaviour, namely the range of its possible actions. Among these, there are e.g. methods for representation. In this way also methods for generalization can be implemented. The question is however how to define such methods. E.g. the aggregation of a set of houses can depend on the distance of the individual houses, on the fact that a street is nearby, ... Which factors are relevant is not easy to determine. One possibility is to use knowledge acquisition techniques to determine generalization rules. Traditionally Knowledge Acquisition this is done by interviewing experts [Weibel, Keller & Reichenbacher 1995]. This process can be automated by methods from Machine Learning. The technique of "Learning from Examples" e.g. uses a set of examples to derive a general rule which describes the structure inherent in the examples. Ideally such techniques are applied when there is no explicit knowledge about the given fact available, or no rules of thumb are known. The examples to feed the learning algorithms can be taken from existing maps. In the learning procedure, e.g. a set of houses can be given as example, whereas the system then has to derive all the relevant objects, the relations between them and thus the criteria when and how to aggregate the buildings to a larger complex.

Generalization highly depends on relations between objects, thus the problem is to define such relations. The paper first presents an approach of supervised learning of object models in terms of an object hierarchy (including attributes and relations of object classes, and corresponding methods) [Sester 1995], which was developed for the application in image and map interpretation. Starting from this approach, a transfer to the generalization in multiple representation is straightforward - since the object models and the methods needed are similar. Thus a concept for learning generalization rules is presented. In the approach the learning program ID3 [Quinlan 1986] is applied.

2 GENERALIZATION OPERATIONS AND DATA STRUCTURES

Generalization bases on distinct operations, like selection, filtering, smoothing, abstraction, aggregation, collapse, scaling and displacement (cf. [Müller, Weibel, Lagrange & Salge 1995], [Beard & Mackaness 1991]).

These operations operate on dedicated data structures, which include all the details necessary for the generalization. This concerns especially the representation of topology (neighborhood, relations, adjacency) - a fact which is obvious for the displacement operator. To this end several data structures are proposed, which can be characterized as raster structures :

- ▹ A triangulation of the given data set ([Bundy, Jones & Furse 1995], [Ruas & Lagrange 1995]) directly reveals the neighborhood of the objects.
- ▹ Another approach applies a raster-vector transformation. In a so-called displacement mountain, the importance of the object, the range and also the direction of displacement can be coded in the gray-values [Jäger 1990].

These representations however take only geometric neighborhood into consideration. Semantic proximity or adjacency over other objects is not considered. For some applications however different types of neighborhood are required.

Thus another structure can be used, namely an object oriented approach, where the object-specific neighborhood is explicitly stored for each object (or object class).

3 APPROACHES FOR TRANSITION BETWEEN MULTIPLE LEVELS OF DETAIL

A well known and popular approach for generalization of line structures is the Douglas-Peucker-Algorithm. Line data structures like the strip-tree or binary line generalization tree (BLG) base on this type of algorithm and guarantee quick access to line objects on various levels of detail.

Concerning generalization of areal features there is an approach by van Oosterom [1995]. He presents the concept for map generalization *on-the-fly*. The aim of his approach is the derivation of a temporary generalization (mainly for the purpose of screen display), thus not the creation of a second, redundant dataset. In order to get quick responses he relies on so-called reactive data structures (i.e. geometric data structure with detail levels). As a data structure for the area partitioning process, he introduces the GAP (generalized area partitioning) tree. Area partitioning starts from the assumption, that each point in the 2D domain belongs exactly to one of the areas, thus there are no gaps or overlaps.

Generalization of an areal object can on one hand be reduced to the generalization of its constituent polygon lines. This however can result in overlaps or gaps when no topological data structure is used. The alternative is to select objects what are to be deleted. In order to prevent having gaps, the now obsolete areas have to be merged to neighboring objects. The author introduces the concept of importance to determine, which objects to drop and how to aggregate them. The importance of an object is defined as a function of its size and type. Thus the aggregation relies on spatial relationships (proximity) and importance of the areal objects. In this way a successive selection and aggregation of the objects can be achieved which finally results in a object hierarchy. The most general (important) object is on the top and the other objects reside in the corresponding levels of the hierarchy. Operations defined on the tree data structure are the calculation of the area and perimeter of any polygon in the hierarchy. This approach proves to be very fast - which was the primary focus it was developed for.

The fact that only one (quite simple) rule is responsible for the aggregation of the areas is considered a drawback. Also the notion of importance seems to depend on certain parameters which have to be tuned in advance.

The concept presented in this contribution aims at a derivation of the relevant rules and parameters directly from the data - and thus independent of the user. He only is responsible for the control and for the provision of meaningful examples.

4 LEARNING RULES FOR RELATIONS

The approach bases on an object-oriented system named FLAVOURS. FLAVOURS is embedded in a programming environment called POP11 (cf. [Barrett, Ramsay & Sloman 1985]) and is an implementation of the MIT Flavors package. POP11 is interpreter-based which allows for a self-generation of program-code. This feature is exploited to a great extent in the prototype learning program, since the rules learned can immediately be applied to the data and thus verified.

The basic assumption is that the rules are either complicated or not easily formulated. Furthermore, deriving rules from the data is easier and more reliable. Still the teacher is there to finally verify and refuse or modify the rules if necessary.

4.1 Learning Structural Object Models

Image and map interpretation needs models in order to interpret the visual information. The problem is to describe appropriate object models - including objects attributes and their relations. Sester [1995] presents an approach of using Machine Learning techniques to derive a model description from given examples. Learning techniques make use of the fact that examples can be named and pointed at quite easily, however it is often not known what the classifying attributes are. So it is left to the learning procedure to determine them.

In order to define the learning task, the objects and their possible relations have to be identified. The actual manifestations of these relations will be learned based on the system "vocabulary", namely the properties and methods of the objects and relations, which is provided. These properties include geometric and topologic functionalities (e.g. size, form, adjacency, relative position, ...). The teacher specifies the concepts to be learned and selects the examples. The task of the learning system is to determine the relevant properties for a given concept and also their values.

In order to solve the task of interpreting given visual information, the system starts with an identification of elementary objects (namely polygons). For the further classification of these objects, the system acquires adequate criteria in the subsequent learning step. The basic idea of the system is to control the process directly by the objects: each objects checks, which methods it has available and whether they can be applied to the given data - namely to the other objects. After all objects have applied their methods and no more changes occur, the teacher can take over the control by starting the learning procedure to acquire new objects or a new object functionality. This in turn can extend the object methods, which they apply to the data. Also there is the possibility of correcting and extending an automatically derived description.

As an illustrative example consider the situation in the picture on the right hand side of Figure 2[1]. Humans can immediately recognize it as an extract of a map with fields and traffic objects. The system however in the first step distinguishes lines and constructs polygons from it.

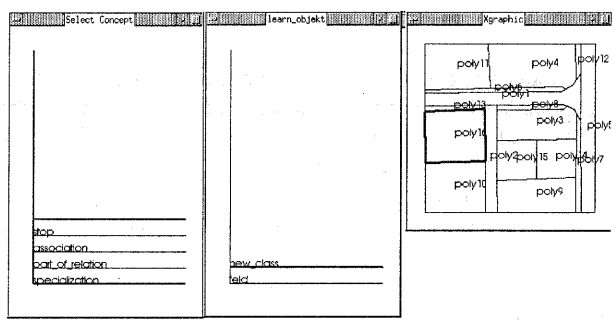

Figure 2: Learning of concepts **traffic** and **field**

In order to learn discriminating criteria for individual object classes the teacher points at different objects and gives a classification. This leads to an automatic creation of new object classes. The characterizing and classifying attributes of the objects are derived by ID3. Thus after the learning step, the systems knowledge has been extended: now the polygons have a new method to apply, namely to differentiate into the new object classes. A successive application of this procedure leads to the recognition of the objects given in Figure 3 (left), namely fields (feld), streets (strasse) and cycle tracks (radweg).

Learning relations allows for the discrimination of so-called *part-of-relations* and *associations*. In order to learn relations, two objects are pointed at, and the teacher indicates whether the relation is valid for these objects or not.

A *part-of-relation* results in the aggregation of objects that share the learned relation. *Associations* have the effect of including more context into the object description. An example for the learning of such a relation is the association between a cycle track and a neighboring street. The teacher points at examples and counter examples for the relation which are stored in an attribute-value list. The first line is a comment line describing the concept to be learned, followed by the attributes; each example with its corresponding attribute values is stored in the subsequent lists.

[1]The figure also visualizes the learning environment.

```
% street_cycle_track connection inside encloses are_parallel
    are_orthogonal common_ell common_tee common_stem
    common_frk common_arw common_njn5 size_diff
    distance_2 left_position top_position common_sides
    same_polytyp  %
[positiv yes no no yes no 1 2 1 0 0 0 2586.363894 43.73397
   left_of top_of 1.03 same_poly] ;;; [radweg5 strasse3]
[positiv yes no no yes no 1 2 0 0 0 0 2940.824027 10.26592
   left_of under 5.63 same_poly ] ;;; [radweg3 strasse3]
[negativ yes no no no yes 0 2 1 0 0 0 1411.443836 76.430477
    right_of top_of 0.04 diff_poly ] ;;; [radweg3 strasse2]
```

From the given examples the following function (decision tree) for the relation is automatically gained by ID3[2]:

```
vars street_cycle_track ;
define street_cycle_track (area1,area2) -> klasse ;
   vars klasse , area1,area2 ;
   undef -> klasse;
   if (are_parallel(area1,area2) ->> val) == "yes" then
      if ( connection (area1,area2) ->> val) == "yes" then
         'positiv' -> klasse;
      elseif (connection(area1,area2) ->> val) == "no" then
         'negativ' -> klasse;
      endif;
   elseif (are_parallel(area1,area2) ->> val) == "no" then
      'negativ' -> klasse;
   endif;
enddefine;
```

This function characterizes that for a neighborhood of streets and cycle tracks a check has to be made as to whether they are parallel and connected - which might be obvious after reading it. Merely inventing such a rule, one might easily have thought of parallelity alone and have forgotten to check for a connection. In the same way, aggregations of objects can be interactively and iteratively gained. E.g. the fact that adjacent fields can be aggregated is learned as a *part-of-relation*.

Figure 3 (left) visualizes the association *street-cycle_track* in dotted lines and the part-of-relation *field-field* in solid lines. The final result - after successive application of the *field-field relation* and also the *street-street relation* - is shown on the right hand side of Figure 3.

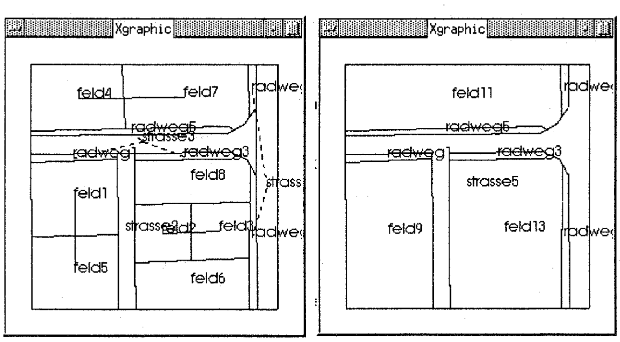

Figure 3: Association *street-cycle_track* in dotted lines; part-of-relation *field-field* in solid lines (left); Final result of interpretation (right)

So in the end a complete scene description evolves, together with a corresponding model characterizing traffic and field objects. The derived model is given in Figure 4.

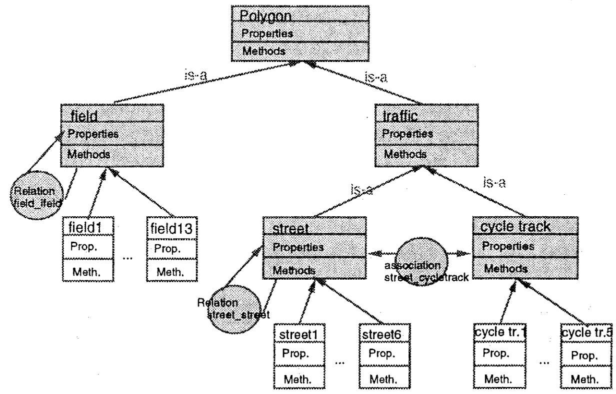

Figure 4: Derived scene model: objects and relations

4.2 Concept for Learning Multiple Representation Rules

The learning facility can easily be applied in multiple representation on two methods:

Learning rules for object presence: Such a rule determines when and if an object is present on a certain level of detail. This can be achieved by pointing at objects and classifying whether the object is existent in the following scale or not. The system then generates a decision tree that determines which attributes are responsible for this representation (e.g. size, form, type).

Learning aggregation rules: In the spirit of van Oosterom [1995] a successive aggregation of the objects has to be performed when going from one scale to the next. In contrast to his method however, the rules for aggregation are not fixed in terms of importance parameters, but are learned directly from the given data set. The expectation is that such rules better reflect the underlying structure in the data. In this way - analogous to the aggregation of fields and streets in the previous example - higher level methods for the generalization of objects can be derived.

4.3 Similarities and Differences between the two Problems

Between the problems model acquisition and multiple representation the following similarities and differences can be found:

Similarities: Both problem domains base on complex object hierarchies. The relations between the individual objects (or object classes) are however object- and task dependent. The system allows to identify these relations and learn corresponding rules depending on the attributes.

[2]This is the automatically derived decision tree in the language POP11. The function is composed of the definition of the function variable *street_cycle_track* and the function itself, enclosed by *define* and *enddefine*

Differences: In the case of model generalization, the identification of the objects is already given (e.g. buildings, parcels of land, streets). Thus the learning starts already with objects instead of mere polygons. However in the course of the learning it might become necessary to create new or intermediate objects. In this way the interpretation capability can be exploited as well.

5 SUMMARY AND CONCLUSION

After an introduction in the importance of multiple representations in GIS, some of the problems when generating such descriptions were presented. Special emphasis was put on the transition between different levels of detail. This has been identified as a learning problem in multiple representation.

Starting from a similar approach in image interpretation, a concept for the learning of generalization rules was presented. This transfer is possible since both domains base on a description of objects in terms of an object-class hierarchy with complex object relations. Depending on the type of object and its methods, different actions can take place. These actions in the first case help to identify and interpret the objects, in the second case they are applied for the derivation of other levels of detail.

References

Barrett, R., Ramsay, A. & Sloman, A. [1985], *POP-11, A Practical Language for Artificial Intelligence*, Ellis Horwood Ltd., Chichester, West Sussex, England.

Beard, K. & Mackaness, W. [1991], Generalization operations and supporting struktures, *in* 'Auto-Carto 10, Technical Papers ACSM/ASPRS Annual Convention', Vol. 6, pp. 29–45.

Bobick, A. & Bolles, R. [1989], Representation space: An approach to the integration of visual information, *in* 'Proceedings of the CVPR 1989', pp. 492–499.

Bundy, G., Jones, C. & Furse, E. [1995], *Holistic generalization of large-scale cartographic data*, in Müller, Lagrange & Weibel [1995], pp. 106–119.

Hahn, M. [1989], Automatic measurement of digital terrain models by means of image matching techniques, *in* 'Proceedings of the 42th Photogrammetric Week', Vol. 13 of *Series of the Institute of Photogrammetry, Stuttgart University*, Stuttgart, pp. 141–151.

Harbeck, R. [1995], Überblick über Konzeption, Aufbau und Datenangebot des Geoinformationssystem ATKIS, *in* E. Kophstahl & H. Sellge, eds, 'Das Geoinformationssystem ATKIS und seine Nutzung in Wirtschaft und Verwaltung - Vorträge des 2. ADV-Symposiums ATKIS am 27. und 28. Juni 1995 in Hannover', Nieders.

Jäger, E. [1990], Untersuchungen zur kartographischen Symbolisierung und Verdrängung im Rasterddatenformat, PhD thesis, Fachrichtung Vermessungswesen, Universität Hannover.

Müller, J.-C., Lagrange, J.-P. & Weibel, R., eds [1995], *GIS and Generalization - Methodology and Practice*, Taylor & Francis.

Müller, J., Weibel, R., Lagrange, J. & Salge, F. [1995], *Generalization: state of the art and issues*, in Müller, Lagrange & Weibel [1995], pp. 3–17.

Quinlan, J. [1986], 'Induction of decision trees', *Machine Learning* **1**(1), 81–106.

Ruas, A. & Lagrange, J. [1995], *Data and knowledge modelling for generalization*, in Müller, Lagrange & Weibel [1995], pp. 73–90.

Sester, M. [1990], Multiscale representation for knowledge based recognition and tracking of objects in image sequences, *in* 'International Archives of Photogrammetry and Remote Sensing', Vol. 28, ISPRS, Comm. III, Wuhan.

Sester, M. [1995], *Lernen struktureller Modelle für die Bildanalyse*, Vol. C441, Deutsche Geodätische Kommission, München.

van Oosterom, P. [1995], *The GAP-tree, an approach to 'on-the-fly' map generalization of an area partitioning*, in Müller, Lagrange & Weibel [1995], pp. 120–132.

Walter, V. & Fritsch, D. [1995], Matching techniques for road network data in different data models, *in* J. Soliman & D. Roller, eds, '28th International Symposium on Automotive Technology and Automation', Automotive Automation Limited, Croydon, England, pp. 633–640.

Weibel, R. [1995], *Three essential Building blocks for automated generalization*, in Müller, Lagrange & Weibel [1995], pp. 56–70.

Weibel, R., Keller, S. & Reichenbacher, T. [1995], Overcoming the knowledge acquisition bottleneck in map generalization: The role of interactive systems and computational intelligence, *in* A. Frank & W. Kuhn, eds, 'Spatial Information Theory', Springer, Berlin, pp. 139–156.

Winkelhausen, H. [1995], ATKIS-Daten als Grundlage eines Planungsinformationssystems für die Region Bodensee-Oberschwaben, *in* 'ATKIS-Daten und ihre Nutzung, DVW-Mitteilungen, Heft 2', pp. 85–96.