GIS and GENERALIZATION

Methodology and Practice

GISDATA 1

Series Editors
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EUROPEAN SCIENCE FOUNDATION
E·S·F

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Taylor & Francis
Publishers since 1798

UK Taylor & Francis Ltd, 4 John St, London WC1N 2ET

USA Taylor & Francis Inc., 1900 Frost Road, Suite 101, Bristol, PA 19007

British Library Cataloguing in Publication Data

A catalogue record for this book is available from the British Library

ISBN 0-7484-0318-3 (cased)
0-7484-0319-1 (paper)

Library of Congress Cataloging in Publication Data are available

Cover design by Hybert Design and Type

Typeset by Keyword Typesetting Services Ltd, Wallington, Surrey

Printed in Great Britain by Burgess Science Press, Basingstoke, on paper which has a specified pH value on final paper manufacture of not less than 7.5 and is therefore 'acid free'.

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Three essential building blocks for automated generalization

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5.1 Introduction

In the past few years, applications of geographic information systems (GIS) have matured, and databases of large size have been built. Users are now beginning to realize the lack of generalization functionality with respect to the development of value-added products from the initial database and the update of existing databases, particularly when multiple scales are involved. Since the majority of results of GIS-based modelling activities is still communicated to the end-user in a graphical form, functions are needed for automated *cartographic generalization*. It must be possible to derive display products from a basic database at arbitrary scale or symbolization, and to maintain good readability. In a digital environment, however, the requirements of generalization extend beyond the original focus on cartography, and include functions for *model generalization* or model-oriented generalization, as will be discussed below.

In order to meet the requirements of today's GIS applications, research needs to tackle various problems. Müller *et al.*, in Chapter 1, have attempted to summarize the state of the art of research in generalization, and outline the problems that would need to be addressed in the future. The discussion here will concentrate on three issues which are considered as particularly important for the progress of generalization research:

- model generalization,
- knowledge acquisition, and
- the evaluation of generalization alternatives.

These elements are considered as 'essential building blocks' for computer-assisted generalization, since they form central prerequisites and seem most needed for a comprehensive solution of generalization in the digital domain. Not all of these problems are on the same level of complexity and functional extent, but they all seem important. The discussion of these three 'pièces de résistance' attempts to identify the subproblems that are involved, and to offer some indications based on our own experience. It is clear, however, that no comprehensive or final solutions can be presented at this point. It is also obvious that these are not the only important issues in generalization. There are other problems that should also receive ample attention, such as the development of more suitable data structures to support map generalization, methods for knowledge representation, or enhanced user interfaces.

5.2 Model generalization

Today, there is a consensus in the research community that, apart from graphics-oriented generalization, there is also a need for model or model-oriented generalization (see Chapter 1).

What does model generalization encompass? One of the major objectives of model generalization certainly is *controlled data reduction* in the spatial, thematic, and/or temporal domain. Data reduction may serve a variety of purposes. A classical aim is to reduce data volume in order to save storage space or speed up computations. Another important reason to reduce the accuracy and resolution of a dataset is the homogenization of different datasets in the process of data integration (or data fusion). For instance, the values of a monthly time-series may need to be reduced to a yearly time interval, in order to develop a unified series. Reclassification or formation of complex objects, which are processes of data reduction in the thematic domain, may be used to prune the solution space for many computations. If data reduction is applied as a filter process (to continuous data), it may be used for the detection and elimination of data errors (Heller, 1990). Besides data reduction, an important objective of model generalization is the *derivation of databases at multiple levels of accuracy and resolution.* This is equivalent to deriving a Digital Landscape Model DLM_2 of reduced contents from an original DLM_1 (Brassel and Weibel, 1988; Müller, 1991a). Finally, of course, model generalization may precede cartographic generalization as a *preprocessing operation.* For instance, the selection of relevant features may be purely model driven and coordinates may be filtered to a resolution corresponding to the target scale of the intended map. This approach corresponds to first reducing a DLM_1 into a DLM_2, and then deriving a Digital Cartographic Model (DCM: Brassel and Weibel, 1988; Müller, 1991a).

It is perhaps interesting to note that, so far, most of the research carried out in model generalization has focused on discrete data, such as objects included in cadastral or topographical maps (Chapter 4; Chapter 18). However, besides discrete objects which can be clearly delineated and discerned, geographic databases also include digital representations of phenomena that vary continuously over space and/or time. Model generalization should, therefore, also include methods to deal with those kinds of data. Examples of continuous variables include terrain, soil salinity, or population density. Commonly, such variables are measured at discrete locations, and the continuous surface is estimated through interpolation. In order to derive a surface of reduced accuracy, the generalization process must start from the original measurements. A possible procedure for model generalization of digital terrain models (DTMs) is demonstrated in Weibel (1992). It is based on an algorithm for iterative filtering of triangulated DTMs developed by Heller (1990). The use of the term 'statistical generalization' by Brassel and Weibel (1988) for what is now commonly known as model generalization was influenced by the work on continuous surfaces reported in Weibel (1992).

In contrast to cartographic generalization, model generalization involves no artistic, intuitive components. Instead, it encompasses probabilistic or even deterministic processes. For the same reasons, engineering-oriented researchers and computer scientists, who frequently had problems understanding the need for artistic compromises in cartographic generalization, should feel more comfortable with model generalization. Thus, one would naturally expect that it should be easier to tackle than its graphics-oriented counterpart. On the other hand, a limiting factor at this time is perhaps that the requirements of model generalization for relevant GIS applications are not yet defined. As in cartographic generalization, different methods will have to be developed for different applications of model generalization. It cannot be expected that 'one size fits all' methods can be devised. It is, however, possible to state some general requirements that should be met by all procedures for model generalization.

- The method should produce predictable and repeatable results.
- The deviations of the resulting model from the original model should be minimized (or at least never exceed a given maximum tolerance).
- The reduction of the data volume should be maximized.
- The integrity (e.g. the topological consistency) of the objects modelled in the original model should not be violated.
- From a user point of view, the procedure should be controllable by as few parameters as possible, and the relation between the input parameters and the result of model generalization should be obvious.
- Finally, efficiency is a further requirement, as model generalization is often aiming at data reduction with the objective of speeding up computations.

Taking the well-known line filtering algorithm described by Douglas and Peucker (1973) as an example, one can observe that it meets the above requirements only partially. It produces predictable and repeatable results, and achieves major reduction factors at little cost in terms of deviations from the original line (McMaster, 1986). Also, it is efficient and can be controlled by a single tolerance value that is easily mappable to the result. The problem, however, is that this algorithm can create self-intersecting lines because no mechanism is included for checking against topological inconsistencies (Müller, 1990). Furthermore, overlaps might result between different lines as a result of filtering each line individually.

The problem with many existing methods for the generalization of spatial data is that they have been developed with no sufficiently focused objective in mind. Although they achieve generalization-like behaviour, it is not always clear whether they can be used for model generalization because they may not fulfil the above requirements. Likewise, many of these algorithms are also not suited for cartographic generalization because they do not pay attention to cartographic principles. The example of the method developed by Douglas and Peucker (1973) is but one of a longer list of possible examples. Nevertheless, these algorithms are used for purposes for which they were never really intended, such as the production of multi-scale databases. It is obvious that future methods for model generalization should adhere more strictly to rigorous criteria that can be used to evaluate their performance, such as the generic requirements outlined above, but also more specific ones.

5.3 Knowledge acquisition

Today, much of the research in cartographic generalization is generally leading in the direction of knowledge-based systems. As a rule, knowledge-based systems derive their power from the knowledge they contain, and not from the particular formalisms and inference schemes they employ. Thus, the formalization of generalization knowledge, known as knowledge acquisition (KA), has become an issue of major importance (Chapter 1). In the computer-science literature (e.g. McGraw and Harbison-Briggs, 1989), the classical methods for acquiring knowledge in the knowledge engineering (KE) process include interviewing experts, learning by being told, and learning by observation. Several supporting techniques have been developed to make knowledge engineering more effective: structured interviews, repertory grids, critical incidents, artificial problems, as well as querying by means of expert system shells. Unlike the primary application domains of today's knowledge-based systems, medical diagnosis, systems configuration, taxonomy, or fault diagnosis, which are based on complex, yet rather well-documented knowledge, generalization involves a great deal of intuition. What makes cartographic knowledge most special, however, is that it is essentially encoded graphically and, thus, hard to describe in words. One rather widely used typology distinguishes between geometric, structural, and procedural knowledge components that are involved in generalization (Chapter 1). Given the specific situation of generalization, it seems natural that the conventional knowledge engineering methods must be refined and extended.

Several different methods are potentially useful for knowledge acquisition in map generalization: conventional knowledge engineering techniques, analysis of text documents, comparison of map series (reverse engineering), machine learning, artificial neural networks, and interactive systems (amplified intelligence). Most previous efforts in knowledge acquisition (e.g. Nickerson, 1991; Mulawa, 1993) have concentrated on the use of conventional KE techniques; that is, they were mainly based on expert interviews. Experience with alternative methods is very limited because the research community is only beginning to tap these new possibilities. On the other hand, it is important to assess the potential of the different approaches and find out about possible strengths and limitations soon. Given the complexity of the generalization process, a combination of KA techniques seems most useful and one would naturally like to direct research efforts to the most promising alternatives.

The author's group are currently conducting studies with several techniques (reverse engineering, amplified intelligence, machine learning, and neural networks) in order to gain some initial experience and structure future research. Based on preliminary results of these studies and on theoretical considerations, the potential of the different alternatives was estimated. A detailed discussion of this effort is given in Weibel (1993). Here, the discussion will concentrate on a summary of the specific characteristics as well as problems that remain to be resolved by future research (see Table 5.1).

As mentioned above, *conventional KE methods*, in particular interviewing techniques, have been used in previous projects. They seem particularly useful for an initial structuring of the problem domain, but also in the long term as a background and complementary strategy for other KA methods. The advantage is that the knowledge is acquired at the source, and thus includes the experts' explanations. However, a fundamental problem encountered in the course of a previous project (Weibel, 1992) is that, because of the holistic nature of the cartographic design process, cartographers find it hard to break down a workflow into distinct actions. Also, they are often reluctant to contribute to technology which they consider is performing clearly below their standards. Similar communication-related problems also exist in knowledge engineering in other fields. Considerable research has thus been carried out on developing communication strategies and interviewing techniques that should help to cope with these problems (McGraw and

Table 5.1 Synopsis of different methods for knowledge acquisition

Method	Time-frame and complexity	Potential use for KA in generalization	Specific characteristics and problems
Conventional KE (interviews, observation of experts at work)	• particularly useful in initial phase, but also long-term • ±low complexity • partial automation possible	• establish initial framework • background for other KA methods • projects in large institutions (NMAs)	• knowledge acquired at the source, includes explanation • needs availability of experts (institutional framework) • experts may be unable or unwilling to explain actions
Analysis of text documents (guidelines)	• only useful during initial phase • low complexity • little automation possible	• initial knowledge base (procedural knowledge) • extensive potential knowledge source	• descriptions often vague • difficult aspects rarely explained in written form • conflicts between rules possible
Analysis of maps: reverse engineering	• only useful during initial phase • ± low complexity • little automation possible	• formalize rules for selection (e.g. Radical Law) • procedural knowledge: semiformal descriptions rather than formal rules	• original generalization idea may be obscured by later updates • final map may not reveal intermediate operations • difficult to determine sequence and relations of operators
Machine learning (ML)	• useful in the mid- to long-term range • high complexity • highly automated	• interpretation of large numbers of facts extracted by reverse engineering or interactive systems • refinement of initial rules	• no previous experience with ML in cartography • so far, lack of suitable data generated by previous investigations • debugging of knowledge necessary

Neural networks (NNs)	• useful in the mid- to long-term range • high complexity • highly automated	• not very useful for KA due to lack of explanation • replacement of algorithmic generalization operators by more holistic approaches • classification (structure recognition)	• very limited experience with NN in cartography • which network topologies work best? • input representation? • choice of training set
Interaction systems (amplified intelligence)	• useful over the entire time-frame • medium to high complexity • automated, but needs human intervention	• evaluation of genealization operators and support facilities (immediate user feedback possible) • KA through interaction logging • integration and testing of knowledge acquired from different sources	• needs involvement of human experts • 'packaging' of operators, interaction mechanisms? • limited experience with interaction logging

Harbison-Briggs, 1989). Another problem that is quite typical of cartography is that skilled cartographers (i.e. potential experts) usually work at large institutions. It is thus often difficult, if not impossible, for outsiders to conduct expert interviews — an institutional framework is needed. Therefore, conventional KE methods are often unattractive for academic researchers who traditionally have carried out most of the research in generalization.

The *analysis of text documents*, particularly of compilation and production guidelines in use at mapping institutions, represents another approach that needs little technological investment. Guidelines provide an extensive potential source of semi-formal knowledge, especially of procedural knowledge. The analysis of such documents thus seems particularly useful during the initial phase of knowledge base development. However, the descriptions contained in production guidelines are usually rather vague, incomplete, and particularly fall short of explaining the difficult aspects of cartographic operations (Chapter 17). In some cases, they are even kept mainly in graphical form, showing illustrations of favourable and unfavourable examples (e.g. SSC, 1987). Another problem is that since guidelines are usually written in a 'sequential' fashion, conflicts between different rules may arise.

As an alternative to analysing text documents, graphical documents — maps — may be studied. This approach attempts to extract generalization knowledge by comparison of the modifications that occur to the individual map elements across the scales of a map series. The strategy has also been dubbed 'reverse engineering', since the process starts with the end-product, and attempts to identify the operations that led to this result. In recent years, high expectations have been raised with respect to this strategy (e.g. Buttenfield *et al.*, 1991; Muller 1991b). However, one must be aware of the fact that the final map is usually the product of a series of complex and convoluted design operations. Thus, apart from technical problems involved with measuring and tracing generalization operators, it is frequently impossible to identify reliably the operations that led to the end-product, and determine their sequence and relation. Also, the original generalization idea may be further obscured by later updates if map sheets of a regular map series are used. Thus, in order to portray generalization in an unbiased fashion, the maps used in a study currently conducted in the author's own group are 'new' maps, having been produced specifically for the purpose of this experiment (Parantainen, 1995). Given the difficulties with this method, it appears that while reverse engineering has been capable of extracting quantitative relations such as the Radical Law developed by Töpfer (1974), the usefulness of this method with respect to formalizing procedural knowledge must be seen in a more conservative fashion (Parantainen, 1995). The output of reverse engineering should be considered as semi-formal descriptions rather than formal rules. These descriptions, in turn, may then support the development of more accurate knowledge using other KA techniques. Also, the analysis of maps can often provide a communication link between the knowledge engineer and the expert cartographer.

Machine learning (ML), in the context of knowledge acquisition for generalization, mainly has its merit as an auxiliary technique. Given the prospect of large numbers of facts to be compiled by reverse engineering, or audit trails produced by interactive systems (see below) in the future, some consideration needs to be given to the way in which these observed but unstructured facts are turned into rules. For humans, it is very quickly impossible to perceive patterns in datasets exceeding the size of just a few elements. ML methods (induction, deduction, concept-based learning, statistical clustering, or neural networks) are capable of generating decision trees or prototype rules that facilitate the formulation of an initial rule set from observed facts (McDonald, 1989). ML can potentially also unveil unknown or unexpected relations and rules. However, ML cannot find any rules that are not 'captured' by the original attributes contained in the facts database. Finally, ML may be used to refine initial rule sets. ML techniques (mainly based on induction) are implemented in several commercial expert system shells as well as in public domain packages. The major impediment to the use of ML thus far has been the lack of suitable data to experiment with the application of ML to cartographic problems. For good results, ML techniques need a large number of reliable facts as input. Also, the decision trees or rules generated by ML need to be tested and possibly debugged, since incorrect or conflicting rules may be inferred.

Neural networks (NNs) or more correctly, artificial neural networks, are a specific form of machine learning (Maren *et al.*, 1990). NNs are capable of learning based on training from given sample situations, but it is hard to actually deduct formal knowledge (i.e. rules, decision trees, etc.) from them. With respect to knowledge acquisition, they are thus not very useful. Nevertheless, neural networks are of interest to generalization due to their great ability in classification and template matching. NNs may be useful for several generalization tasks, as is discussed by Werschlein and Weibel (1994). The most straightforward application is the use of NNs for the classification of map feature attributes (i.e. thematic generalization). Another potential use of NNs is in the context of structure recognition, where they could replace statistical methods for the classification of 'structure signatures' (Buttenfield, 1991) with a potentially more robust approach. A third area to which NNs might be applicable in generalization is the evaluation of alternative generalization solutions produced by different methods and/or different parameters (see the next section). Perhaps the most interesting NN application of all, however, is in replacing current algorithmic generalization operators with more holistic solutions. For instance, algorithmic operators for line generalization are split up into subprocesses such as simplification, smoothing, and enhancement, while a suitable caricature can often only be obtained through a combination of processes. NNs may potentially overcome this discretization.

As with machine learning, however, practically no previous experience exists with the use of NNs in cartography. Initial work with NNs in line generalization performed by Werschlein and Weibel (1994) suggests that the performance of NNs primarily depends on three points: the scheme that is used to represent the input data, the topology of the network, and the choice of samples used to train the network. Among these factors, the choice of input representation is of overriding importance. The representation of the input data essentially dictates what patterns can be inferred by the neural network. In raster-based generalization (e.g. of land use maps), input representations can be restricted to simple raster data structures, since generalization is basically performed by reclassification of cells, while geometry does not change. In vector mode generalization, however, input representations cannot be restricted to the basic data structures used by algorithmic methods (e.g. simple strings of x/y coordinates). Basic representations must be enriched by additional transformations (e.g. line curvature) in order for the neural network to be able to infer reliably shape modifications between input and output. Werschlein and Weibel (1994) provide a discussion of possible input representations for cartographic lines.

The last alternative for knowledge acquisition is the use of *interactive generalization systems*, also termed *amplified intelligence* (Weibel, 1991). The basic idea is that interactive systems could be equipped with a facility for logging the interactions of expert users with the system. The analysis of the resulting interaction logs (also called audit trails) is then expected to lead to the formulation of rules. This author proposed this approach several years ago (Weibel, 1989, 1991); other researchers are now pursuing similar strategies (e.g. McMaster and Mark, 1991). The concept is appealing, even more so since the same set-up could also be used for testing of existing and new generalization operators and support facilities, as well as the integration and testing of knowledge that is acquired through different methods. On the other hand, systems that carry some potential to act as a platform for knowledge acquisition are only beginning to emerge (e.g. Lee, 1993), and a number of difficult problems still need to be resolved before this approach can be exploited successfully. Formats for interaction logs (what actions are being logged, when, and how?) and mechanisms for editing these logs must be developed. The 'packaging' of operators — that is, the level at which the user can control them — will significantly influence the interaction logs that can be produced. Furthermore, the characteristics of map features must be determined and logged as well (e.g. line sinuosity, relation to neighbouring features, etc.), in order to identify why generalization operators have been applied and what triggered these actions. Once interactive systems are being used for interaction logging experiments, they are bound to generate a vast number of facts describing the flow of operations during generalization. It will therefore be necessary to use machine learning tools in an attempt to interpret these unstructured facts. One expects, however, that the automated interpretation of interaction logs alone will not suffice; further interviews and session observations (possibly by video taping) of the experts at work are needed as complementary techniques. Finally, it should be mentioned that audit trails can have more direct uses besides knowledge acquisition, which can also be beneficial in a production environment. The most immediate use of interaction logs can be seen in the creation of macros for action replay. Audit trails may also be used for 'generalization by example': parameters are interactively trained and logged for one or several smaller but representative regions of the original map, and subsequently applied to the entire map automatically.

In conclusion of this section, one can observe that a variety of methods can be explored for KA in generalization that have the potential of complementing each other in terms of the types of knowledge that may be formalized, the technological efforts involved, the degree to which experts are involved in the KA process, and their current maturity. Conventional KE techniques and analysis of guidelines seem most valuable in the context of research conducted by or in close collaboration with mapping agencies. The position of reverse engineering should be seen conservatively; its best use may be as a means of bringing together researchers from the academic sector and practising cartographers. Machine learning and neural networks represent novel techniques in cartography that should be studied extensively by academic research. Interactive systems offer the best potential for the integration and testing of knowledge from various sources and should therefore be pursued even if future research shows that their value for knowledge acquisition is limited.

5.4 Evaluation of generalization alternatives

While some research was conducted in the late 1970s and early 1980s to develop geometric measures for an assessment of line simplification (e.g. McMaster, 1986), the development of methods for evaluating generalization results has received very little attention since then. It is only now being realized that such evaluation methods are an important component and even a prerequisite of knowledge acquisition. Evaluation is needed at three different stages of the generalization process.

- *A priori evaluation* is necessary prior to the actual knowledge acquisition process. It includes the selection of suitable study areas and test datasets, and helps in assessing the performance of potential expert cartographers as well as distinguishing examples of good solutions from poor work which should not be considered for knowledge formalization. The latter aspect is particularly crucial for the selection of suitable training samples for NN applications. Often, some of the input materials may still be in analogue form and may need to be digitized first.
- *A posteriori evaluation* is needed to compare and rank different generalization alternatives: for instance, those that are generated by different generalization operators or sequences. It also involves the assessment of existing algorithms and techniques for generalization (both generalization operators and support facilities). In principle, the methods that can be used for a posteriori evaluation are the same as those for a priori evaluation.
- *Ad hoc evaluation* is required to control the automated generalization process as a means of continuous evaluation. It includes the task of conflict resolution between contradicting rules at run time and thus forms part of the meta-knowledge of a knowledge-based system. Some approaches such as the so-called genetic algorithms involve the automated generation of large sets of alternatives using different parameters in order to find the best solution (Armstrong, 1993). Ad hoc evaluation is needed in this case to prune the solution space and to determine the optimal solution.

The overall process of evaluation involves two tasks. First, *specifications* must be established of what defines a 'good' or 'acceptable' generalization for a given map. It is only against such requirements that a generalization result can be assessed. These specifications, of course, will depend on the constraints of the generalization process, such as the purpose and scale range of the given maps, and the quality of the input data. Apart from criteria relating to the quality of the graphic output, other factors such as efficiency, robustness, and ease of use are relevant when evaluating digital methods. As a second task of evaluation, the actual *assessment* must then attempt to determine the degree to which the specifications are met by a given result.

The study of the traditional cartographic literature can provide a natural starting point for the development of methods for evaluating generalization alternatives. Many textbooks and teaching notes (e.g. SSC, 1987) make use of 'good' and 'poor' examples to explain particular concepts of generalization. An investigation of that literature can provide some initial hints for the development of specifications as well as methods for assessment. Further input can be gained by studying the quality assurance procedures currently in place at mapping agencies for manual production. And finally, a study of the literature on quality assurance and benchmarking in non-cartographic disciplines such as industrial or software engineering could perhaps furnish further insight about methods for the assessment of non-quantifiable processes.

Since generalization involves highly intuitive components, it cannot be expected that any evaluation procedure can be purely objective. Definitely, there are criteria that can be assessed objectively such as violations of topological relations, but other aspects such as 'overall clarity of the map image' are very hard to express rigorously. These objective and subjective components of generalization can be expressed by a number of quantitative and qualitative criteria. In general, quantitative measures relate to objective properties of generalization and design, while qualitative descriptions are used to capture subjective aspects. However, note that 'quantitative' and 'objective' are not synonymous: minimal dimensions, for instance, can be specified in a strictly quantitative way, but the actual values used for a particular map are often left to specific subjective preferences. Likewise, qualitative descriptions of subjective components can also be made in a more quantitative fashion, for instance, by using a grading scheme and associated weighting factors. Both quantitative and qualitative criteria must first of all allow us to compare different generalization alternatives (among themselves and/or against a solution that is considered optimal), and eventually make it possible to judge and rank different solutions consistently. The question is then how objective and subjective aspects of generalization are characterized in a meaningful way: at which stage of the evaluation and in which way should quantitative measures form the basis of a qualitative assessment?

A project currently under way in the author's group is the development of a methodology for the evaluation of generalization alternatives (Ehrliholzer, 1995). This includes the definition of a prototype report format that integrates quantitative and qualitative criteria, as well as sets (or modules) of measures and qualitative aspects that are considered relevant for different types of generalization problems (depending on map purpose, scales, feature classes, and data types). The expectation is that, in a particular evaluation situation, a specific report format could be compiled from relevant modules, and the resulting values for the report items weighted according to the preferences defined for the project.

Quantitative measures have the purpose of supporting the assessment by determining computationally to what degree design specifications are violated and/or how closely an 'optimal' solution (e.g. a digitized template of a manually produced version) is matched. Possible measures include the following:

- **Global measures**. These may include the degree of generalization and whether it is constant over the entire map (measured by means of feature density and feature clustering), adherence to the Radical Law, and the ratio of foreground to background (b/w ratio).
- **Geometrical measures**. A first group of geometrical measures is needed to highlight cases where the *minimal dimensions* are violated (i.e. objects that are too small, objects that are too close, segments that are too short, etc.). A second group is required to determine the amount of *distortion*, that is, deviation from the *shape* of the representation in the original map or in a map that is used as a reference (e.g. a manually produced map that is considered as a good solution). McMaster (1986) describes a number of such measures for linear objects. Similar measures need to be developed for point and area objects. Various measures are readily available for this purpose from the literature in the fields of computer vision as well as geography and cartography (e.g. Pavlidis, 1978; Austin, 1984, to name but two possible sources).
- **Topological measures**. The purpose of these measures is to identify violations of topological relations that need to be maintained from the original map. These include the detection of self-intersections of lines as well as intersections among different lines, overlapping objects, and adjacency relations that are violated (e.g. a house moved to the other side of a road as a result of simplifying the road).
- **Software-related measures**. In order to measure the productivity gain that can be accomplished as a result of automation, several aspects of software performance must be assessed, including CPU time, person hours spent on a particular generalization task, equipment hours and cost, entire duration of the project, and possible map update cycle. The person hours, to some degree, reflect the ease of use and the robustness of the generalization software. These aspects, along with other more

evasive software-related factors, such as work satisfaction, must be assessed further in the qualitative part of the evaluation procedure.

The implementation of a rigorous procedure for *qualitative evaluation* is inherently more difficult to achieve than the formulation of quantitative measures. Apart from the study of the relevant literature mentioned above, a close collaboration with different experts is necessary to develop a suitable checklist and questionnaire that will eventually lead to a common form of assessment. Ideally, it should be possible to compare the evaluations of different generalization alternatives even if they are performed by different experts.

The author believes that the format of a standardized questionnaire and checklist that asks the evaluating expert to give grades (e.g. 1 to 5) for a variety of assessment items is the most effective way to characterize rigorously and consistently subjective aspects of generalization, and also provides the most direct form of integration with quantitative measurements. In order to allow integration, qualitative questions must match the categories of the quantitative assessment. For instance, as a counterpart of global quantitative measures, qualitative aspects on the global level, such as 'maintenance of the overall character of the original map', can be assessed. Similar questions can be formulated as counterparts of geometrical, topological, and software-related measures, where factors such as 'ease of use' are largely subjective.

Of course, in some cases, an expert will find it hard to assign a grade which can only reflect an average for a particular assessment question. It must be possible for him/her also to document specific problems, typical situations, or details that are handled particularly well. A possible solution is the use of hypermedia techniques to implement an evaluation report, allowing integration of screen snapshots, annotations, and sketches as a means of illustrating specific points. The question is then also whether the assessment should be performed completely in the digital domain (e.g. by means of a visual overlay of scanned manual maps and digital solutions). Finally, it should be noted that the distinction of the effects of generalization from those of other cartographic processes may pose a serious problem. For instance, it may be that, in principle, the elements of a particular map have been generalized adequately, yet an inappropriate symbolization of the individual elements may negatively affect the clarity of the map (Baumgartner, 1990). In such a case, it may be very hard to determine what mistakes have contributed to the poor appearance of the resulting map.

5.5 Conclusions

It appears that research in generalization has entered a new stage. In contrast to earlier years, when research in generalization usually concentrated on the development of narrow, special-purpose solutions, current research strategies are attempting to approach the overall problem in a more comprehensive way. Strategies such as amplified intelligence are pursued that can integrate existing methods to exploit their combined potential. Generalization is no longer viewed as a purely graphics-oriented process, but consideration is also given to reduction, reclassification, and filtering processes in the numerical domain, that is, to model generalization. Finally, attempts are being made to base generalization on a better understanding of the processes that are involved, leading towards the development of knowledge-based approaches.

As is often the case when a new stage is reached in a research domain, there are more questions than answers. At this point, it is first of all important to ask the right questions, and develop a concept about where the answers could be found most probably. Based on the example of three issues that we have identified as crucial for progress of research — model generalization, knowledge acquisition, and the evaluation of generalization alternatives — we have attempted to identify problems and potential solutions for research.

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