AUTOMATIC OBJECT EXTRACTION FOR CHANGE DETECTION AND GIS UPDATE

Stefan Hinz

Remote Sensing Technology, Technische Universitaet Muenchen, 80 333 Muenchen, Germany
Stefan.Hinz@bv.tu-muenchen.de

KEY WORDS: Object Extraction, Image Understanding, Evaluation, Disaster Management

ABSTRACT:

In this paper we will revise the recent developments in the field of automatic object extraction for change detection and GIS update under different aspects: (1) level of automation; (2) available sensors and image characteristics; (3) effectiveness and processing time; and (4) verification/editing and quality of results. For most applications, none of these aspects can be considered isolated from the others. We will exemplify the importance of these aspects by the recent efforts made, in order to support the management and prevention of natural hazards and civil crises, e.g. caused by floodings or earthquakes.

1. INTRODUCTION

Aerial and satellite imagery plays a major role for the population and update of GeoDatabases, and many approaches have been developed to automate the involved processes to a large extent. Especially, semi- and fully automatic extraction of roads and buildings has gained much attention over the last decades. We will first give a short overview of recent developments in the field of automatic object extraction with focus on roads and buildings, before we put special emphasis on object extraction in the context of change detection and disaster management. We discuss the issues of object extraction under different aspects, in particular:

- Level of automation
- Available sensors and image characteristics
- Effectiveness and processing time
- Verification/editing and quality of results

For most applications, none of these aspects can be considered isolated from the others. We will exemplify interaction and differing importance of these aspects by the recent efforts made to support the management and prevention of natural hazards and civil crises, e.g. caused by floodings or earthquakes. This application is in particular interesting since the importance of the above points varies over time before, during, and after such an event.

2. AUTOMATIC OBJECT EXTRACTION – ISSUES AND DEVELOPMENTS

The automatic extraction of objects like roads and buildings in natural environments is one of the challenging issues in photogrammetry and computer vision. Natural environments are often characterized by a high complexity of the imaged scene. Factors having great influence are, for instance, the number of different objects, the amount of their interrelations, and the variability of both. Moreover, each factor – and thus the scene complexity – is related to a particular scale. To accommodate for such factors, techniques like detailed modeling, (automatic) contextual reasoning, and internal evaluation of intermediate results have proven to be of great importance over the past years. It is clear that these techniques must be integral parts of an extraction system to attain reasonably good results over a variety of scenes.

For the following discussion of recent work, we selected four important trends seen in object extraction over the last years and grouped the approaches accordingly: (1) Integration of multiple views; (2) Integration of functional and temporal characteristics; and (3) Integration of scale-space behavior.

2.1 Integration of multiple cues

Much recent work deals with integration and simultaneous processing of multiple cues for object extraction. Typical multi-cue approaches rely on combination of:

- different filters responses (textures, topographic sketch, ...)
- different spectral characteristics
- different sensors (images, laser data, SAR, …)
- image information and external data (GIS)

A major challenge for processing multi-cue data is the handling of uncertainties during object extraction. Cues derived from different sources should support and supplement each other. In practice, however, numerous conflicting cues appear in case of reasonably complex scenes. The derivation and utilization of confidence measures is thus a key issue to provide a basis for deciding which hypothesis may overrate another and which should be eliminated.

An interesting earlier approach regarding the role of multiple-cue processing is given in (Tupin et al., 1999). They deal with finding consistent interpretations of SAR scenes (Synthetic Aperture RADAR). Different low level operators are applied to generate cues for one or more object classes (e.g. road *and* river), represented by a confidence value characterizing the match with the designated object classes. All confidence values are combined in an evidence-theoretical framework to assign unique semantics to each primitive attached with a certain probability. Finally, a feature adjacency graph is constructed in which global knowledge about interrelations between objects (road segments form a network, industrial areas are close to cities,...) is introduced in form of object adjacency probabilities. Based on the probabilities of objects and their relations the final scene interpretation is formulated as a graph labeling problem that is solved by energy minimization.

For building extraction, cues are typically derived from overlapping images, high resolution surface models (DSMs) and GIS data. The DSM may stem from aerial laser scanner data, but also from matching aerial images with high overlap percentage. A straightforward approach for combining surface and cadastral data is given in (Durupt & Taillandier, 2006). Although supporting or conflicting hypotheses are not analyzed in very much detail, it is impressive to see that their system achieves reasonable results for hundreds of buildings and runs on an operational basis. (Rottensteiner et al., 2005; Rottensteiner, 2006) extract low-level features for building reconstruction from multispectral images and surface models. Building parameters are estimated in a consistent way by considering geometrical regularities employing soft constraints, while false and conflicting hypotheses are eliminated through a robust estimation. Recent approaches make also use of the distinct 3D characteristics of buildings and some of them focus also on facades, which can be included by acquiring terrestrial data. (Dorninger & Nothegger, 2007) present an approach for 3D segmentation, which can make full use of high resolution 3D points from laser scanning (up to 20 points per m²) or image matching showing also at least partially the vertical facades. The approach relies on a full 3D representation of planes in parameter space and clustering the points in this space. Results for points from laser and image data prove that very high quality models can be generated. (Zebedin *et al.* 2006, 2007) show how facade planes derived from dense 3D points can be refined by sweeping the planes and projecting them into all views where they are visible. This does not only lead to very good estimates for the plane, but also for the texture as demonstrated by a number of convincing examples. An alternative to close the gap of missing structures of facades in classical nadir data and missing structures from roofs in terrestrial data is to capture the scene with an oblique looking sensor. (Hebel & Stilla 2007) show this for the case of an oblique-viewing laser scanner. Yet, also for this approach, a high precision multi-aspect registration of point clouds is necessary for further processing the data.

A clear tendency can be seen that also recent approaches for road extraction integrate 3D information. (Clode *et al*. 2007), for instance, use high resolution LIDAR height and intensity data to delineate the road geometry in 3D. Primary road hypotheses are generated by classification employing colour intensities and height gradients. The result is then vectorized by convolving a complex-valued disk (so-called Phase Coded Disk) with the image. The Phase Coded Disk represents basically the local features of the road model. Center line and width of the road are obtained from the magnitude image while the direction is determined from the corresponding phase image. (Hinz 2004a, 2004b) employs a DSM and multiple-view imagery to extract urban road networks. The extraction is based on a detailed scale-dependent road and context model to deal with the high complexity of this type of scenes. The corresponding extraction strategy is subdivided into three levels: level 1 comprises the analysis of context, i.e., the segmentation of the scene into the urban, rural, and forest areas as well as the analysis of context relations, e.g., the determination of shadow areas and the detection of vehicles; level 2 includes the detection of homogeneous ribbons as preliminary road segments in coarse scale, collinear grouping thin bright road markings in fine scale, and the construction of lanes and carriageways from groups of road markings and road sides; level 3, finally, completes the road network by fusing road segments detected in overlapping images, iteratively closing gaps in the extraction, and exploiting the network characteristics to generate a topologically complete road network. A key feature of the approach is the incorporation of a scheme for internal evaluation. Hypotheses generated during extraction are internally evaluated so that their relevance for further processing can be assessed.

Typically, also multispectral information can be exploited since, for both airborne sensors and spaceborne sensors, the acquisition of multi-spectral data in the visible domain has reached a resolution regime, in which multi-spectral analysis can substantially support the extraction. For instance, (Mena & Malpica, 2005) and similarly (Zhang & Couloigner, 2006) use colour information to derive various statistical and textural parameters. Classifying an image based on these features yields potential road segments, which are cleaned and skeletonized into road center axes. Such approaches show limitations when applied to images of low resolution compared to the object size. Dealing with mixed pixels is thus an important issue if roads are to be mapped using satellite images. To cope with this, (Bacher & Mayer, 2004, 2005) developed a two-step strategy. First, training information for a supervised classification is obtained from an initial step of road extraction with very strict parameter settings. The results are fed into a multispectral classification to generate a so-called roadclass-image, which can be interpreted as an additional channel. These multi-channel data are processed simultaneously with the line- and network-based road extraction approach of (Wiedemann & Hinz, 1999). By means of this strategy, the linear properties of roads in each channel are exploited and – if available – supplemented with area-based colour information. An alternative is shown in (Ziems *et al.*, 2007), where colour information is employed to better identify false alarms when determining potential errors in existing road databases, e.g., if GIS road axes run through fields or bushes. To this end, a statistical analysis of the colour distribution derived from potential road areas in comparison with trained distributions is carried out.

2.2 Integration of functional and temporal properties

With the increasing availability of airborne videos and highly overlapping photogrammetric image sequences, also the integration of temporal features becomes feasible. These show great potential to add very valuable information additionally to the geometric and radiometric properties of objects. This trend can be seen in particular for road extraction where first approaches for road mapping by activity analysis and car tracking were recently developed. The work by (Pless 2006), for instance, aims at detecting temporal changes in stabilized airborne videos. It is based on a generic scheme to discern static background from active foreground on the basis of eigenvalue analysis. Especially in the case of dense traffic, active image regions correspond to the main roads. While this approach is mainly designed for the analysis of inner city areas, the Bayesian car tracking system by (Koch *et al.* 2006) is able to fuse multiple car tracks from different flight paths. By employing a comprehensive Bayesian model for the sensor characteristics as well as the detection and fusion scheme, the inherent uncertainties in the physical and mathematical sensor modelling and track hypothesis generation are handled in a very consistent way. As final step, the – potentially interrupted – car tracks are transformed into objects space and fused to eventually delineate a precise and topologically intact road network.

2.3 Integration of scale-space characteristics

The importance of incorporating the scale space behaviour of objects into automatic extraction approaches has been recognized already in the 1990s. It has been shown that different levels of image resolution can be linked to certain levels of abstraction of knowledge (Mayer & Steger, 1998). The extraction benefits from using different scales, since initial hypotheses can be efficiently formed in coarse scale, which are validated and tested in fine scale. Vice versa, intermediate results obtained in fine scale can be evaluated with respect to their importance for the global functional properties of the objects described in coarse scale.

Recently, (Drauschke *et al.* 2006) analyzed the scale-space behaviour of building features. They show that there is no particular optimum scale for building reconstruction, yet they observe a stability of the features over certain intervals in scale-space. Thus, a low number of selected scales seems to be sufficient for building extraction. In the same spirit (Forberg, 2004; Forberg & Mayer, 2006) show how the behaviour of buildings in different scale-spaces can be used for their generalization in 3D. They use so-called scale-space events in the morphological and curvature space to reduce the level of detail of buildings for cartographic generalization. For road extraction, usually two (Baumgartner *et al.* 1999, Hinz & Baumgartner 2003) but in some special cases also three (Mayer 1998, Hinz 2004a) different scales have been used. While the coarse scale, i.e., 2m to 4m, allows to extracting roads based on their fundamental characteristics and functional properties – such as curvilinear shape, network characteristics, and optimum routes between certain places – the fine scale, i.e., less than 50 cm, enables detailed analysis and precise geometric delineation of the road layout. (Heuwold 2006, Heuwold & Pakzad 2006, Heuwold *et al.* 2007) aim at generalizing this issue for a quasi-continuous scale space in 2D. The results shown in (Heuwold 2006) are promising for the case of parallel linear structures as they often appear in the context of road extraction, but they also show that this kind of fundamental research is far from being solved in general.

Many of the discussed aspects are highly relevant for the current activities directed towards the design and implementation of an image understanding system for disaster management at the German Aerospace Center (DLR). The scientific challenges are moreover accompaigned with requirements of an operational environment, reasonable processing times and efficient workflows. The next section will outline this in more detail.

3. OBJECT EXTRACTION FOR DISASTER MANAGEMENT

There is no doubt, that remote sensing methods can provide valuable support for activities directed towards the prevention of natural hazards and managing the consequences of natural disasters. Techniques for automatic object extraction and change detection consequently play a major role in this context. However, in addition to the scientific and methodological challenges, the approaches to object extraction must be integral part of a comprehensive system of actions, documentations and planning activities during, after and also before a (potential) disaster. This is only possible if the image understanding methods are embedded into well-defined strategies for supporting the preparedness and prevention of hazards, for fast reaction in case of disasters, as well as for damage documentation, planning and rebuilding of infrastructure after disasters.

Remote sensing can contribute significantly to all these components in different ways, especially because of the large coverage of remotely sensed imagery and its global availability. Time, however, is the overall dominating factor once a disaster has hit a particular region. This becomes manifest in several aspects: firstly, available satellites have to be selected and commanded immediately. Secondly, the acquired raw data has to be processed with specific signal processing algorithms to generate images suitable for interpretation, particularly for Synthetic Aperture Radar (SAR) images. Thirdly, the interpretation of multi-sensorial images, extraction of geometrically precise and semantically correct information as well as the production of (digital) maps need to be conducted in shortest time-frames to support crises management groups. While the first two aspects are strongly related to the optimization of communication processes and hardware capabilities (at least to a large extend), the main methodological bottleneck is posed by the third aspect: the fast, integrated, and geometrically and semantically correct interpretation of multi-sensorial images.

Concerning the automated extraction of objects, special focus is on the extraction, analysis and characterization of infrastructural objects like roads and buildings due to their importance for the immediate planning and implementation of emergency actions. In the following, we concentrate on the detection of *intact* road networks under the constraints of an effective disaster management. This means, that those parts of the road network, which are not detected by the system, should be regarded as destroyed and not accessible for rescue and evacuation teams anymore. A similar approach for buildings can be found in (Rehor & Bähr, 2006), where the goal is to decide if buildings in laser-scanner data are damaged, e.g., by an earth quake, and what kind of damage has occurred.

In the following, we link the description of the system's underlying concept and methodologies with the discussion of the issues of object extraction posed at the beginning: (1) system design and different levels of automation; (2) automatic extraction under the light of available sensors and data characteristics; (3) effectiveness/processing time and the need for internal evaluation; and (4) quality of the final results and verification/post-editing.

3.1 System design: Different levels of automation

At the moment, fully automatic approaches for object extraction must still be regarded as a subject of fundamental research, and they seem not to be able to find their way into operational work flows in the very near future. On the contrary, semi-automatic approaches seem more likely to be useful in operational applications. Automatically achieved results nonetheless may provide a basis for efficient checking, editing and improving.

Hence, the framework for the automated detection of intact roads from multi-sensorial imagery is conceptually divided into three main parts. The first part comprises the (fully-) automatic extraction of roads. The results will be of course not 100% complete and correct. It follows therefore an internal evaluation of the automatically achieved results as second module. This provides measures about the reliability of road parts, which should guide an operator during editing the results. This editing phase – the third part – involves user-assisted tools to support effective checking and completing the results.

3.2 Automatic extraction: Requirements through characteristics of available sensors and images

To enable a fast reaction after a disaster, special emphasis should be put on the exploitation of multi-sensorial optical and SAR satellite images, as the current and in particular the future availability of these sensors allows to acquiring such images nearly everywhere and at any time. Optical images show strong advantages concerning the radiometric image quality if they were taken during good weather and illumination conditions. On the other hand, SAR holds some prominent advantages over optical images, which are in particular helpful in crisis situations. SAR is an active system that can operate during day and night. It is also nearly weather-independent and, moreover, during bad weather conditions, SAR is today's only operational system available at all. However, as coherent imaging technique, SAR images are affected by the well-known speckle noise as well as image derogations due to radar shadow and layover. The imaged objects are thus subject to drastic changes in their appearance depending on the radar illumination parameters. The challenges of man-made object extraction from SAR data, in particular roads and buildings, can be viewed in (Wessel & Hinz 2004, Sörgel et al. 2006). The need for and the potential of further developments in this area has been recognized years ago, but it will be even more important in the future as consequence of the high potential of new airborne and spaceborne sensor systems such as TerraSAR-X, TanDEM-X, or Radarsat-2.

Driven by the technological advances, recent work in the field of automatic object extraction shows the importance of developing models and strategies that combine evidence from various sources in a sound statistical framework. The evidence may stem, e.g., from multiple views, different sensors, or external data. The approach of (Wessel & Hinz, 2004; Wessel, 2006; Hedman et al., 2006, 2007, 2008) may serve as example for road extraction from single and multiple SAR images. It models the sensor- and context-dependent appearance of roads and is meanwhile adapted to Bayesian decision theory in order to consistently incorporate multiple SAR images and knowledge about the appearances and relations of objects. The first step consists of a line extraction in each image, followed by attribute extraction. Based on these attributes the uncertainty of each line segment is estimated statistically, followed by an iterative fusion of these uncertainties supported by context information and sensor geometry (see Fig. 1). On the basis of a resulting uncertainty vector each line obtains an estimation of the probability that the line really belongs to a road. The final step includes the generation of a road network by calculating optimal paths through the weighted graph of line segments and connections between them. Figure 2 shows the result of employing context information about forest and urban areas into the extraction of roads. The borders of these areas serve as seed points for generating the road network, while the interior of these areas is excluded. An evaluation with manually digitized reference has shown that a completeness of approx. 70% can be reached when accepting a correctness also of approx. 70%.

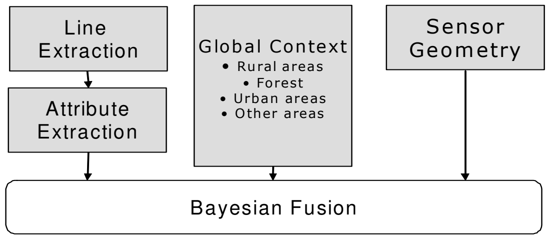

Figure 1. Bayesian fusion module and its input data

As expected, both correctness and completeness increase when applying a similar version of this extraction system to optical images. (The only difference between the two versions is the procedure for primitive extraction and evaluation.) Figure 3 visualizes the result of road extraction on an optical image of similar resolution and similar scene complexity. Here, a completeness of approx. 85% is reached while the correctness is still over 90%. The example shown later in Fig. 6 illustrates, though, that even a low percentages of cloud coverage may influence the quality of the results. We refer the interested reader to (Mayer et al. 2006), where more details and a thorough comparison and discussion of different automatic road extraction approaches applied to optical images can be found.

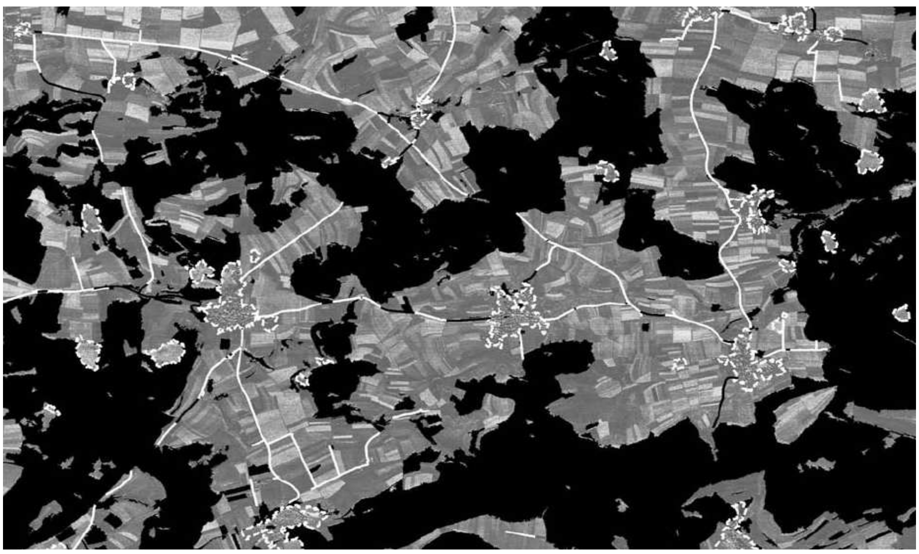

Figure 2. Result of road extraction from SAR X-/L- pair employing global context (from (Wessel 2006)). White lines: extracted roads; black lines: missing roads; dotted lines: context area "urban" (seed point for extraction); black areas: context area "forest".

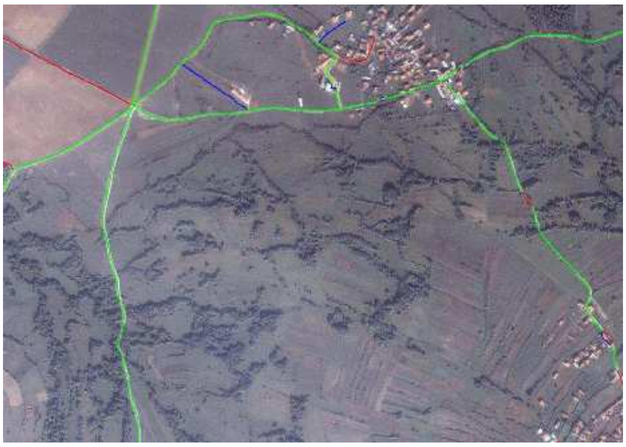

Figure 3. Road extraction from optical satellite image (IKONOS pan-sharpened). Green: correct extraction; red: missing extraction; blue: false alarms. For more details, see (Mayer et al. 2006)

3.3 Internal Evaluation: Effectiveness and processing time

An automatic object extraction system as exemplified in the previous section may not be expected to deliver absolutely perfect results and, thus, for meeting predefined application requirements, a human operator must inspect the automatically obtained results. In order to speed up the time- and cost-intensive inspection, the system should provide the operator with confidence values characterizing the system's performance – a so-called internal evaluation. This information can only be derived from redundancies within the underlying data or the incorporated object knowledge. In this context, "object knowledge" means knowledge that is purely described by the object model and not by other external data. Therefore, internal evaluation is strongly linked to the extraction process. The results of internal evaluation are particularly important if the extraction results are combined with other data, e.g., if they are fused with results from other extraction approaches or if they are used for the update of GIS data. On the other hand, they are also very useful for guiding a human operator during post-editing the results of an automatic extraction. In practice, however, this is rarely the case.

In order to achieve a highly independent evaluation, we utilize "knowledge redundancies" in the form of object properties that have not been used during the extraction (see (Hinz & Wiedemann, 2004) for details). Usually, these properties relate to global characteristics of objects which can be hardly used during bottom-up object extraction processes. An extracted road network, for instance, must be in accordance with some typical global network characteristics: few connected components, no clusters of junctions outside urban areas, convenient connections between various places depending on the terrain type etc. Such properties are used in (Hinz & Wiedemann, 2004) to evaluate the reliability of portions of the network with a fuzzy-set theoretic approach.

To allow a quick and effective inspection by a human operator, the evaluated road segments are displayed in an overview window and categorized into three classes: green (to be accepted), yellow (to be checked), and red (to be rejected). In addition, the average quality of the evaluated network and the distribution are displayed (see Figure 4).

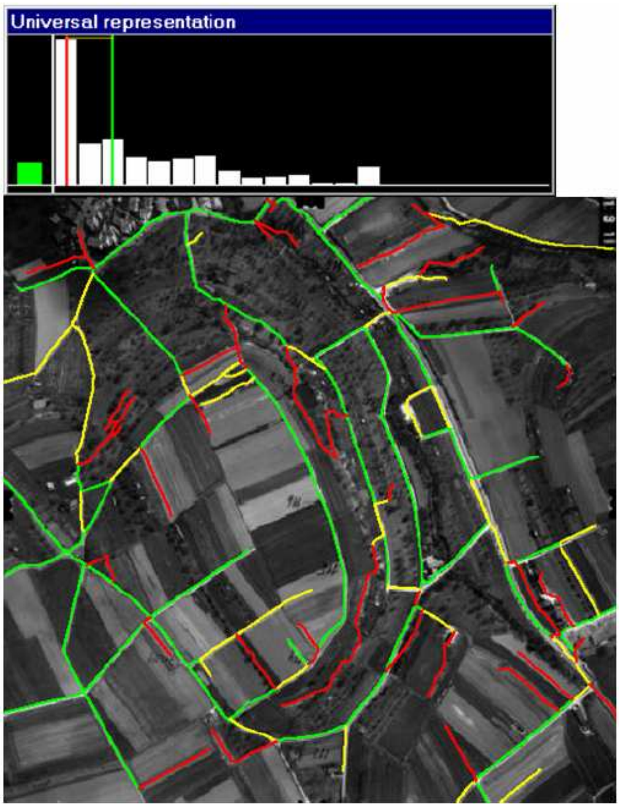

Figure 4. Overview of self-diagnosis. Top: Length-weighted histogram of evaluation scores (left-most bar indicates mean value = *green* in this example), thin vertical lines indicate thresholds between categories. Bottom: Overview window

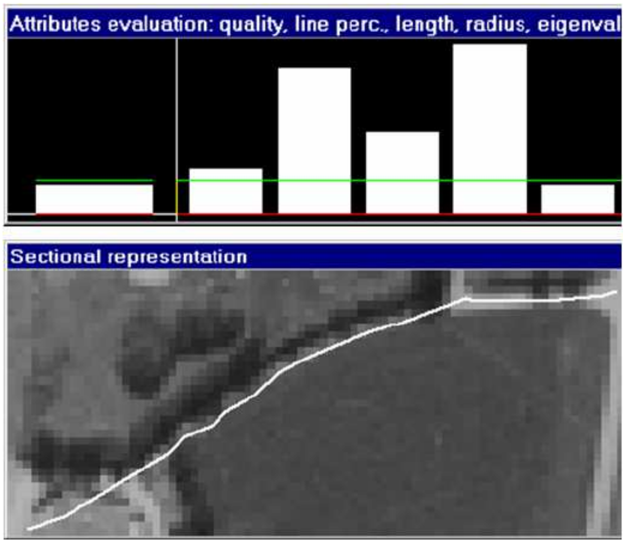

Figure 5. Detailed inspection of evaluation results of a specific portion of the road network. Bars indicate results of evaluation for each criterion involved ([0 ; 1]).

Whenever a particular road section is sought to be inspected in more detail, it can be selected in a separate cutout to investigate the evaluation details (see Figure 5). Based on the visualization and the quality information, the operator may decide how to handle a particular road section — whether it should be retained, deleted, or edited.

To analyze the reliability of self-diagnosis, we matched the internally evaluated results to a manually plotted reference (see (Hinz & Wiedemann, 2004)). The comparison showed that almost every road section of the green category is a correctly extracted road (above 90%). The self-diagnosis also detects "false alarms" in the extraction with high reliability (80% – 90%). Considering the evaluation of yellow-labeled road sections one can state that these parts of the road network should indeed be investigated by a human operator because the correctness values are generally lower and vary to a notable extent (50% – 75%). It is furthermore interesting to observe what would happen if an operator had checked *exclusively* the *yellow-labeled* road sections. Under the assumption that a human operator is able to discern correct and wrong detections without any error, the correctness of the overall result would remain in the range of 95%, while the amount of editing drops down significantly: only 25% to 50% of the whole road network need to be checked.

However, it is important to note that one can improve only the correctness through employing this scheme for internal evaluation. Completeness can only be increased when identifying potential gaps in the extraction and closing them. To this end, the system provides user-assisted tools for road extraction.

3.4 User-assisted extraction: Manual interaction vs. quality of the results

Semi-automatic, i.e., user-assisted, tools have the advantage that the quality of the results is guaranteed, because a human operator controls the data acquisition process and prevents errors online. Yet the overall benefit of such systems depends not only on their sophisticated algorithms but also on adequate tools for editing. Quite a lot of promising approaches for semi-automatic road extraction have been presented and analyzed in the last decades. Two groups of approaches can be distinguished: Road trackers and path or network optimizers. Road trackers need a starting point on the road and a second point to define the direction of the road. These approaches have quite a long history, see e.g. (Groch, 1982; McKeown & Denlinger, 1988; Vosselman & de Knecht, 1995; dal Poz et al., 2000; Baumgartner et al., 2002, poggio et al., 2005). Path optimizers are designed to find an optimum path between two points on a road. Typical methods include dynamic programming (Fischler et al., 1981) or active contour models, so-called "snakes", (Kass et al., 1988; Neuenschwander et al., 1995; Grün & Li, 1997). In (Butenuth, 2006, 2007) the path optimization is extended to full networks with a predefined topology, which has strong advantages for user-assisted road extraction, see for instance the results shown in (Butenuth, 2008).

Road trackers and path optimizers are characterized by complementary properties: Road tracking is usually based on a road profile selected by a user for a particular road to be traced. In this way, the specific radiometry of this road is included into the procedure. This is in particular helpful when different roads of varying appearance should be extracted. Such appearance-based constraints are commonly not included in path optimization. Snake algorithms, for instance, need to be fed with a generic image energy, which is derived through more or less complex filtering operations like a gradient amplitude map, Laplacian map, distance transform, etc. On the other hand, road tracking algorithms do not include any topological information about the connectivity of the road network. Disturbances due to background objects or noisy images (like SAR images) lead often to very wiggling tracks or even useless results. In such situations, snakes and in particular network snakes show clear advantages over tracking procedures, since the geometric and topologic constraints involved in the optimization process act as regularization for the noisy data.

Figure 6 shows an example for user-assisted tracking of a main road in an IKONOS image taken during the Elbe flooding in Germany, 2002. The yellow parts were traced automatically, while simple user clicks were asked at the blue positions. Here, the operator had to decide whether tracking should just continue or interactive editing is necessary. Tracking could continue at all interruptions except the one shown in the cut-out of Fig. 6. It illustrates a situation, where cutting-off the tail of the track and manual digitizing of a short road section is necessary due to the occlusion of a small cloud. A detailed description of this algorithm and the variety of options for user interaction can be found in (Baumgartner et al., 2002). Figure 7 shows the same tracking algorithm applied to a RADARSAT SAR image. As can be seen, much more interactions were necessary due to the worse image quality. Yet the importance of introducing topologic constraints comes clear, when applying snake algorithms and network optimization procedures to such images. Although, compared to road tracking, more initial user clicks were necessary to roughly digitize the paths and set up the correct topology of the network (see Fig. 8), the rest of the optimization of the whole network was achieved completely automatically. This appeared to be much more convenient than supervising the tracking in such situations.

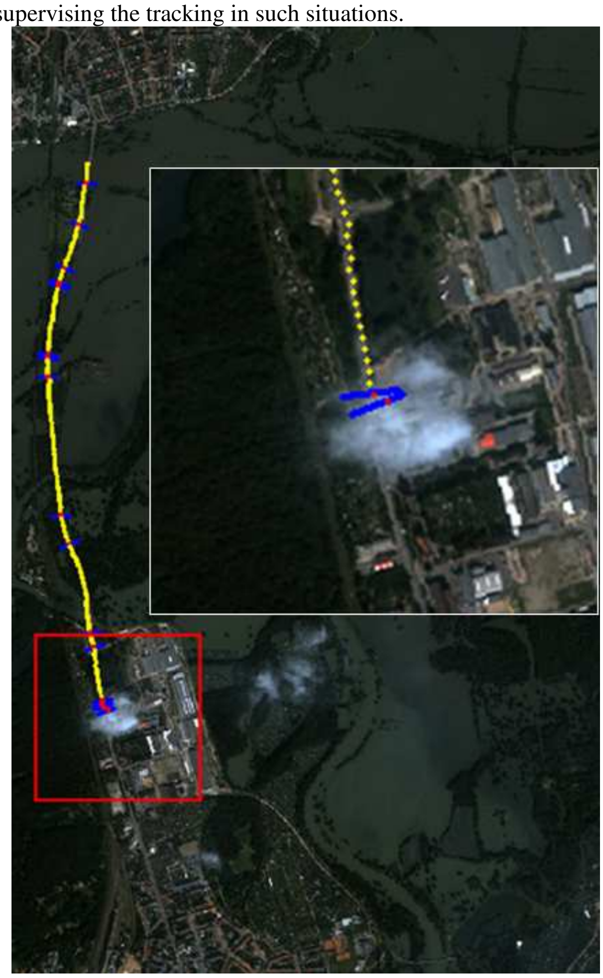

Figure 6. User-assisted road tracking in an IKONOS image taken during the Elbe flooding in Germany, 2002. Yellow: tracked road sections; blue: user clicks.

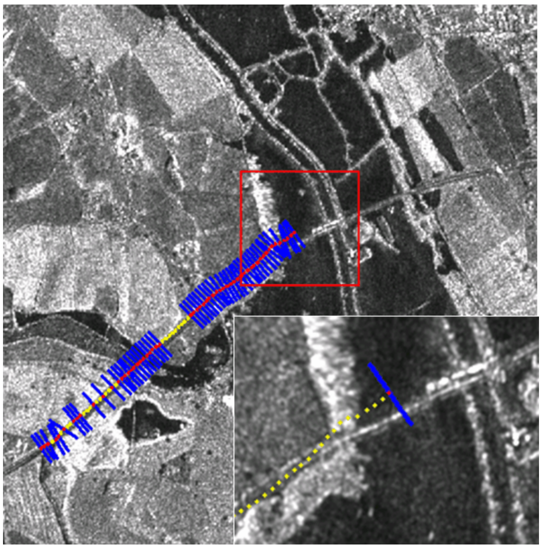

Figure 7. User-assisted road tracking in aRADARSAT SAR image. Yellow: tracked road sections; blue: user clicks.

Figure 8. Road network optimization in a SAR image. Top: Interactive initialization; bottom: result after optimization.

A thorough comparison of road tracking and path/network optimization in terms of effectiveness and acquisition quality has not been conducted up to now. Nonetheless, behavior and acquisition time of the tracking algorithm of (Baumgartner et al., 2002), for instance, has been extensively tested and evaluated (Schölderle, 2005). Neglecting the time for data handling, geo-coding, and so forth, we experienced a reduction in plotting time of up to 50% depending on the complexity of the scene. For most rural scenes the time effort was reduced to 50%-70%. For more complex scenes, i.e., for urban or suburban areas, the performance of the tracking tool was too poor to compete with snake algorithms. As expected, in urban areas the automatic tracking failed very often, and putting the tracker back on the road every few seconds is quite annoying and time consuming.

Both strategies of semi-automatic road extraction have complementary advantages and limitations. Ideally, it would be possible to combine both in a unique framework. From a methodological point of view, this would include that appearance-based components of road tracking should be incorporated into the optimization framework of network snakes. This would help to utilize more knowledge about the objects during optimization. Furthermore, it would allow to evaluating the results obtained with snake algorithms – an issue still not solved for the general case so far. Although first attempts have been undertaken, a sound solution has not been found for this so far. Nor it seems possible to estimate from the data which strategy for user-assisted road extraction is promising for a given scene and which not, so that the better one could be provided to an operator. Therefore, our current concept for road extraction in the context of disaster management is designed to provide both modules to the operator and hand over the choice of the appropriate procedure to him.

4. CONCLUSION AND OUTLOOK

Especially under the light of today's and tomorrow's available optical and SAR satellite systems, the development of integrated approaches for object extraction from multi-sensorial images are a substantial element to support fast and accurate information extraction. To this end, models and extraction strategies need to be developed that integrate the different geometric and radiometric sensor characteristics attached with stochastic models to accommodate for the inherent modeling and measurement uncertainties. Despite of encouraging results, there are still many fundamental questions to be solved for object extraction, e.g.:

- Which type of modelling is appropriate to capture the variability of the object classes, especially under the light of the success of appearance-based approaches?
- Which relations between objects can support object extraction, and which are more or less clutter?
- Is it possible to design a strategy that adapts itself to the given extraction without loosing control over the computational load? Or, is it better to start with a monolithic strategy and incorporate dynamic elements or use generic search algorithms and apply heuristics to control the search space?
- Which decisions should be handed over to a human operator and which can be done by the computer?

The challenges for research and development in this area are laid out and well-known. Time will show whether they can be successfully met in the long run.

ACKNOLEDGEMENT

We like to thank all members of the DeSecure team for their support in pushing the project forward and preparing the example data, and especially M. Butenuth and D. Frey for providing the extraction results of tracking and network snakes. Thanks go also to EuroSDR, in particular Helmut Mayer, who organized the test of automatic road extraction approaches.

REFERENCES

Bacher, U. & Mayer, H., 2004, Automatic road extraction from IRS satellite images in agricultural and desert areas. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35 (B3), 1055–1060.

Bacher, U. & Mayer, H., 2005, Automatic road extraction from multispectral high resolution satellite images. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 36 (3/W24), 29–34.

Baumgartner, A., Hinz, S.,Wiedemann, C., 2002. Efficient Methods and Interfaces for Road Tracking. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. 34(3B), 28–31.

Baumgartner, A., Steger, C., Mayer, H., Eckstein, W., Ebner, H., 1999. Automatic Road Extraction Based on Multi-Scale, Grouping, and Context. Photogrammetric Engineering and Remote Sensing 65 (7): 777–785.

Butenuth, M., 2006, Segmentation of Imagery Using Network Snakes. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 36-3, 1-6.

Butenuth, M., 2007, Segmentation of Imagery Using Network Snakes. Photogrammetrie – Fernerkundung – Geoinformation, 1/2007: 7-16

Butenuth, M., 2008, Topology-preserving network snakes. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37-B3A.

Clode, S., Rottensteiner, F., Kootsookos, P. and Zelniker E., 2007, Detection and vectorization of roads from LIDAR data, Photogrammetric Engineering & Remote Sensing, 73: 517–536.

Dorninger, P. & Nothegger, C., 2007, 3D segmentation of unstructured point clouds for building modeling. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35 (3/W49A), 191–196.

Drauschke, M., Schuster, H.-F. and Förstner, W., 2006, Detectability of buildings in aerial images over scale-space. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35 (3), 7–12.

Durupt, M. & Taillandier, F., 2006, Automatic building reconstruction from a digital elevation model and cadastral data: An operational approach. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35 (3), 142–147.

Fischler, M. A., Tenenbaum, J. M., Wolf, H. C., 1981. Detection of Roads and Linear Structures in Low-Resolution Aerial Imagery Using a Multisource Knowledge Integration Technique. Computer Graphics and Image Processing 15: 201–223.

Forberg, A., 2004, Generalization of 3D building data based on a scale-space approach, In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 35-B4, 194-199.

Forberg, A., & Mayer, H., 2006, Simplification of 3D Building Data. Zeitschrift für Vermessungswesen (131) 3, 148-152.

Groch, W.-D., 1982. Extraction of Line Shaped Objects from Aerial Images Using a Special Operator to Analyse the Profiles of Functions. In: Computer Graphics and Image Processing, vol. 18: 347-358.

Grün, A. & Li, H. (1997): Semi-Automatic Linear Feature Extraction by Dynamic Programming and LSB-Snakes. In: Photogrammetric Engineering & Remote Sensing, vol. 63(8): 985-995.

Hebel, M. & Stilla, U., 2007, Automatic registration of laser point clouds of urban areas. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 36 (3/W49A), 13–18.

Hedman, K., Hinz, S., Stilla, U., 2006, A Probabilistic Fusion Strategy Applied to Road Extraction from SAR Data. In: International Archives of Photogrammetry, Remote Sensing, and Spatial Information Sciences, Vol. 36-3, 55-60.

Hedman, K., Hinz, S. and Stilla, U., 2007, Road extraction from SAR multi-aspect data supported by a statistical context-based fusion. In Proceedings of IEEE-ISPRS Workshop URBAN 2007, on CD.

Hedman, K., Hinz, S. and Stilla, U., 2008, Evaluation of a statistical fusion approach developed for automatic road extraction from multi-view SAR images. In: Proceedings of IGARSS'08, Boston, USA (to appear).

Heuwold, J., 2006, Verification of a methodology for the automatic scale-dependent adaptation of object models In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(3), 173–17.

Heuwold, J. & Pakzad, K., 2006, Automatic scale-dependent adaptation of variable object models. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 36 (W40), 65–70.

Heuwold, J., Pakzad, K., Heipke, C., 2007, Scale behaviour prediction of image analysis models for 2D landscape objects. In International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36 (3/W49A), 43–50.

Hinz, S., 2004a Automatische Extraktion urbaner Straßennetze aus Luftbildern. PhD thesis, Deutsche Geodätische Kommission, C (580), Munich, Germany.

Hinz, S., 2004b, Automatic road extraction in urban scenes – and beyond. In: International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 35, (B3), 349–354.

Hinz S. & Wiedemann, C. 2004, Increasing efficiency of road extraction by self-diagnosis. Photogrammetric Engineering and Remote Sensing, 70(12): 1457–1466.

Hinz, S., & Baumgartner, A., 2003, Automatic Extraction of Urban Road Networks from Multi-View Aerial Imagery. In: ISPRS Journal of Photogrammetry and Remote Sensing, 58/1-2: 83 - 98.

Kass, M., Witkin, A., Terzopoulos, D., 1988. Snakes: Active contour models. In: International Journal of Computer Vision, vol. 1: 321–331.

Koch, W., Koller, J. and Ulmke, M., 2006, Ground target tracking and road map extraction. ISPRS Journal of Photogrammetry and Remote Sensing, 61 (3-4), pp. 197–208

Mayer, H., 1998. Automatische Objektextraktion aus digitalen Luftbildern. Habilitation, Deutsche Geodätische Kommission, C (494), Munich, Germany.

Mayer, H., Hinz, S., Bacher, U. and Baltsavias, E., 2006, A test of automatic road extraction approaches. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 36 (3), 209–214.

Mayer, H. & Steger, C. 1998, Scale-Space Events and Their Link to Abstraction for Road Extraction. ISPRS Journal of Photogrammetry and Remote Sensing, 53 (2): 62–75

McKeown, D., Denlinger, J., 1988. Cooperative Methods For Road Tracking In Aerial Imagery. In: Computer Vision and Pattern Recognition, 662–672.

Mena, J. & Malpica, J., 2005. An automatic method for road extraction in rural and semi-urban areas starting from high resolution satellite imagery. Pattern Recognition Letters, 26, 1201–1220.

Neuenschwander, W., Fua, P., Szekely, G., Kübler, O., 1995. From ziplock snakes to velcro surfaces. In: Grün, A., Kübler, O., Agouris, P. (eds.), Automatic Extraction of Man-Made Objects from Aerial and Space Images, Birkhäuser Verlag, Basel, 1995, 105–114.

Pless, R., 2006, Detecting roads in stabilized video with the spatio-temporal structure tensor. Geoinformatica, 10 (1): 39–56.

dal Poz, A., Gyftakis, S., and Agouris, P., 2000. Semiautomatic road extraction: Comparison of methodologies and experiments. In: Proc. ASPRS 2000, , Washington, D.C., on CD

Rehor, M. & Bähr, H.-P., 2006, Segmentation of damaged buildings from laser-scanning data. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35 (3), 67–72.

Rottensteiner, F., Trinder, J., Clode, S., Kubik, K., 2005. Using the Dempster Shafer method for the fusion of LIDAR data and multi-spectral images for building detection. Information Fusion 6 (4): 283-300.

Rottensteiner, F. 2006, Consistent estimation of building parameters considering geometric regularities by soft constraints. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35 (3), 13–18.

Schölderle, F. 2005, Praxistest eines Straßentrackers. Technical Report, PF 05-01, Remote Sensing Technology, TU Muenchen, Germany.

Soergel, U. Thoennessen, U. Brenner, A. Stilla, U., 2006, High-resolution SAR data: new opportunities and challenges for the analysis of urban areas. Radar, Sonar and Navigation, 153(3): 294-300.

Tupin, F., Bloch, I., Maitre, H., 1999, A first step toward automatic interpretaion of SAR images using evidential fusion of several structure detectors. IEEE Transactions on Geoscience and Remote Sensing 37(3): 1327–1343.

Vosselman, G., de Knecht, J., 1995. Road tracing by profile matching and kalman filtering. In: Grün, A., Kübler, O., Agouris, P. (eds.), Automatic Extraction of Man-Made Objects from Aerial and Space Images, Birkhäuser Verlag, Basel, 1995, 265–274.

Wessel, 2006, Automatische Extraktion von Straßen aus SAR-Bilddaten. PhD thesis, Deutsche Geodätische Kommission, C (600), Munich, Germany.

Wessel, B. & Hinz, S., 2004. Context-supported road extraction from SAR imagery: Transition from rural to built-up areas. Proceedings of EUSAR 2004, Ulm, Germany, 399–402.

Wiedemann C. & Hinz, S., 1999, Automatic extraction and evaluation of road networks from satellite imagery. In International Archives of Photogrammetry and Remote Sensing, 32 (3/2W5), 95–100,

Zebedin, L., Klaus, A., Gruber, B. and Karner, K., 2006, Facade reconstruction from aerial images by multi-view plane sweeping. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35-3, 31-36.

Zebedin, L., Klaus, A., Gruber, B. and Karner, K., 2007, Facade reconstruction from aerial images by multi-view plane sweeping. Photogrammetrie – Fernerkundung – Geoinformation, 1/07: 17–24.

Zhang Q. & Couloigner I., 2006. Automated road network extraction from high resolution multi-spectral imagery. In ASPRS 2006 Annual Conference, Reno, Nevada, on CD.

Zhou, J., Bischof, W. F., Caelli, T., 2005, Robust and Efficient Road Tracking in Aerial Images. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 35 (3/W24), 35–40.

Ziems, M., Gerke, M., Heipke C., 2007, Automatic road extraction from remote sensing imagery incorporating prior information and colour segmentation, In International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36 (3/W49A), 141–148.