URBAN ROAD NET EXTRACTION INTEGRATING INTERNAL EVALUATION MODELS

Stefan Hinz and Albert Baumgartner

Chair for Photogrammetry and Remote Sensing,
Technische Universität München, Arcisstraße 21, 80290 München, Germany
{Stefan.Hinz, Albert.Baumgartner}@bv.tum.de – www.RemoteSensing-TUM.de

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ABSTRACT

This paper focuses on internal quality measures for automatic road extraction from aerial images taken over urban areas. The motivation of this work is twofold: Firstly, any automatic system should provide the user with a small number of values indicating the reliability of the obtained results. This is often referred to as "self-diagnosis" and is in particular a crucial part of automatic image understanding systems. Secondly, and more important in the scope of our research, a system designed for the extraction of man-made objects in complex environments (like roads in urban areas) inherently implies many decisions during the extraction process. Such decisions are highly facilitated when both low level features and high level objects are attached with confidence values indicating their relevance for further processing. The basic idea for defining evaluation criteria from which the confidence values can be calculated is to split the components of a semantic object model into two different types. The model components of the first type are used for extracting features, i.e., parts of the object, and the components of the other type serve as criteria for evaluating the quality of the extracted features. For guaranteeing an unbiased evaluation one has to ensure that model components belonging to different types are independent from each other (at least theoretically). We illustrate this concept by our system for road extraction in urban areas. Examples are given for both low level features like lines and ribbons as well as higher level features like lanes and road segments.

1 INTRODUCTION

From a practical point of view, research on automatic road extraction in urban areas is mainly motivated by the importance of geographic information systems (GIS) and the need for data acquisition and update for GIS. This demand is strikingly documented in the survey on 3D city models initiated by the European Organization for Experimental Photogrammetric Research (OEEPE) a few years ago (Fuchs et al., 1998). Applications of road extraction in urban areas include analyses and simulations of traffic flow, estimation of air and noise pollution, street maintenance, etc.

From the scientific perspective, the extraction of roads in complex environments is one of the challenging issues in photogrammetry and computer vision, since many tasks related to automatic scene interpretation are involved. In order to cope with the high complexity of urban scenes, our extraction system integrates detailed knowledge about roads and their context using explicitly formulated models. The road model includes, for instance, small sub-structures such as markings but also knowledge about the global network characteristics of roads, while the context model describes relations between roads and other objects, e.g., buildings casting shadows on the road or cars occluding parts of a lane. This makes it possible to extract roads even if their appearance is heavily affected by other objects.

The work presented in this paper focuses on the development of internal quality measures for automatic road extraction. The motivation of this specific aspect within an object extraction system is twofold: Firstly, any automatic system should provide the user with some values indicating the reliability of the obtained results. This is often referred to as "self-diagnosis" (Förstner, 1996) which is a crucial part of automatic image understanding systems, in particular, when designed for practical applications. Secondly, and more important in the scope of our research, confidence values also play an important role for the reliability of the extraction itself, since they highly facilitate inevitable decisions which have to be made during the extraction process. Consider, for instance, competing road hypotheses extracted from multiple overlapping images which must be combined into an unique road network. The correct selection becomes much easier when the hypotheses are attached with confidence values indicating their quality and relevance for further processing. Such situations often occur within image understanding systems designed for the extraction of cartographic objects from natural scenes. Hence, the development of methodologies for internal quality control was identified as a major research issue by the scientific community (see the editors' note in (Baltsavias et al., 2001)).

In the next section, we briefly review work on automatic road extraction with emphasis on approaches dealing with urban environments and approaches employing internal quality measures. In Sect. 3, we continue with a short overview of our extraction system before describing details of the incorporated extraction and evaluation methods in Sect. 4. Finally, the achieved results are analyzed and discussed (Sect. 5).

2 RELATED WORK

Besides many user- or map-guided approaches, also numerous automatic approaches have been developed (see articles in (Gruen et al., 1995, Gruen et al., 1997, Baltsavias et al., 2001)). Most of these efforts are directed towards the extraction of roads in rural areas. Approaches designed to process satellite or low resolution aerial images generally describe roads as curvilinear structures (Heller et al., 1998, Wang and Trinder, 2000, Wiedemann and Ebner, 2000) while those using large scale imagery (i.e., a ground resolution less than 1 m) model roads mostly as relatively homogeneous areas satisfying certain shape and size constraints (Ruskoné, 1996, Zhang and Baltsavias, 1999, Baumgartner et al., 1999, Laptev et al., 2000).

Compared to the relatively high number of research groups focussing their activities on rural areas, only few groups work on the automatic extraction of roads in urban environments. Here, the road network is often modelled as a combination of grids with a rather regular mesh size, i.e., the size of one building block. (Faber and Förstner, 2000), for instance, rely on directional information of lines extracted from scanned maps or low resolution images. They use local directional histograms to segment regions showing similar grid orientation. In (Price, 2000) multiple high resolution images and Digital Surface Models (DSM) are combined to extract the urban road grid in complex, though stereotypical, residential areas. After manual initialization of two intersecting road segments defining the first mesh, the grid is iteratively expanded by hypothesizing new meshes and matching them to image edges. During final verification, the contextual knowledge is exploited that streets are elongated structures whose sides may be defined by high objects like buildings or trees. Thus, so-called extended streets (few consecutive road segments) are simultaneously adjusted by moving them to local minima of the DSM while isolated and badly rated segments are removed. The internal evaluation of a road segment mainly depends on the edge support found during hypothesis matching. However, ratings of single segments may be altered during verification of extended streets, which seems justified since this verification is carried out from a more global perspective on the object "road".

An interesting approach regarding the role of internal evaluation is employed in the system of (Tupin et al., 1999) for finding consistent interpretations of SAR scenes (Synthetic Aperture RADAR). In a first step, different low level operators with specific strengths are applied to extract image primitives, i.e., cues for roads, rivers, urban/industrial areas, relief characteristics, etc. Since a particular operator may vote for more than one object class (e.g. road *and* river), a so-called focal and non-focal element is defined for each operator (usually the union of real-world object classes). The operator response is transformed into a confidence value characterizing the match with its focal element. Then, 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 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 labelling problem that is solved by energy minimization. In (Tönjes et al., 1999), scene interpretation is based on a priori knowledge stored in a semantic net and rules for controlling the extraction. Each instance of an object, e.g., a road axis, is hypothesized top-down and internally evaluated by comparing the expected attribute values of the object with the actual values measured in the image. Competing alternative hypotheses are stored in a search tree as long as no further hypotheses can be formed. Finally, the best interpretation is selected from the tree by an optimum path search.

In summary, many approaches derive confidence values from low level features such as lines or edges. In the following steps the values are propagated and aggregated providing eventually a basis for the final decision about the presence of the desired object. This procedure may cause problems since the evaluation is purely based on local features while global object properties are neglected. Therefore, some approaches introduce additional knowledge (e.g., roads forming a network or fitting to "valleys" of a DSM) at a later stage when more evidence for an object has been acquired. All mentioned approaches have in common that they use one predefined model for simultaneously extracting *and* evaluating roads. Due to the complexity of urban areas, however, it is appropriate to use a flexible model for extraction and evaluation, which can easily adapt to specific situations occurring during the extraction, e.g., lower intensities and weaker contrast in shadow areas. Before describing our evaluation methodology in more detail we give a brief summary of the extraction system.

3 SYSTEM OVERVIEW

Our system tries to accommodate aspects having proved to be of great importance for road extraction: By integrating a *flexible, detailed road and context model* one can capture the varying appearance of roads and the influence of background objects such as trees, buildings, and cars in complex scenes. The *fusion of different scales* helps to eliminate isolated disturbances on the road while the fundamental structures are emphasized (Mayer and Steger, 1998). This can be supported by considering the function of roads connecting different sites and thereby forming a fairly dense and sometimes even regular network. Hence, exploiting the *network characteristics* adds global information and, thus, the selection of the correct hypotheses becomes easier. As basic data, our system expects high resolution aerial images (resolution < 15 cm) and a reasonably accurate DSM with a ground resolution of about 1 m. In the following, we sketch our road model and extraction strategy. For a comprehensive description we refer the reader to (Hinz et al., 2001a, Hinz et al., 2001b).

3.1 Road and Context Model:

The road model illustrated in Fig. 1 a) compiles knowledge about radiometric, geometric, and topological characteristics of urban roads in form of a hierarchical semantic net. The model represents the *standard case*, i.e., the appearance of roads is not affected by relations to other objects. It describes objects by means of "concepts", and is split into three levels defining different points of view. The *real world* level comprises the objects to be extracted: The road network, its junctions and road links, as well as their parts and specializations (road segments, lanes, markings,...). These concepts are connected to the concepts of the *geometry and material* level via *concrete* relations (Tönjes et al., 1999). The geometry and material level is an intermediate level which represents the 3D-shape of an object as well as its material describing objects independently of sensor characteristics and viewpoint (Clément et al., 1993). In contrast, the *image* level which is subdivided into coarse and fine scale comprises the features to detect in the image: Lines, edges, homogeneous regions, etc. Whereas the fine scale gives detailed information, the coarse scale adds global information. Because of the abstraction in coarse scale, additional correct hypotheses for roads can be found and sometimes also false ones can be eliminated based on topological criteria, while details, like exact width and position of the lanes and markings, are integrated from fine scale. In this way the extraction benefits from both scales.

The road model is extended by knowledge about context: So-called context objects, i.e., background objects like buildings or vehicles, may hinder road extraction if they are not modelled appropriately but they substantially support the extraction if they are part of the road model. We define global and local context:

***Global context*:** The motivation for employing global context stems from the observation that it is possible to find semantically meaningful image regions – so-called *context regions* – where roads show typical prominent features and where certain relations between roads and background objects have a similar importance. Consequently, the relevance of different components of the road model and the importance of different *context relations* (described below) must be adapted to the respective context region. In urban areas, for instance, relations between vehicles and roads are more important since traffic is usually much denser inside of settlements than in rural areas. As (Baumgartner et al., 1999), we distinguish *urban*, *forest*, and *rural* context regions.

***Local context*:** We model the local context with so-called *context relations*, i.e., certain relations between a small number of road and context objects. In dense settlements, for instance, the footprints of buildings are almost parallel to roads and they give therefore strong hints for road sides. Vice-versa, buildings or other high objects potentially occlude larger parts of a road or cast shadows on it. A context relation "occlusion" gives rise to the selection of another image providing a better view on this particular part of the scene, whereas a context relation "shadow" can tell an extraction algorithm to choose modified parameter settings. Also vehicles occlude the pavement of a lane segment. Hence, vehicle outlines as, e.g., detected by the algorithm of (Hinz and Baumgartner, 2001) can be directly treated as parts of a lane. In a very

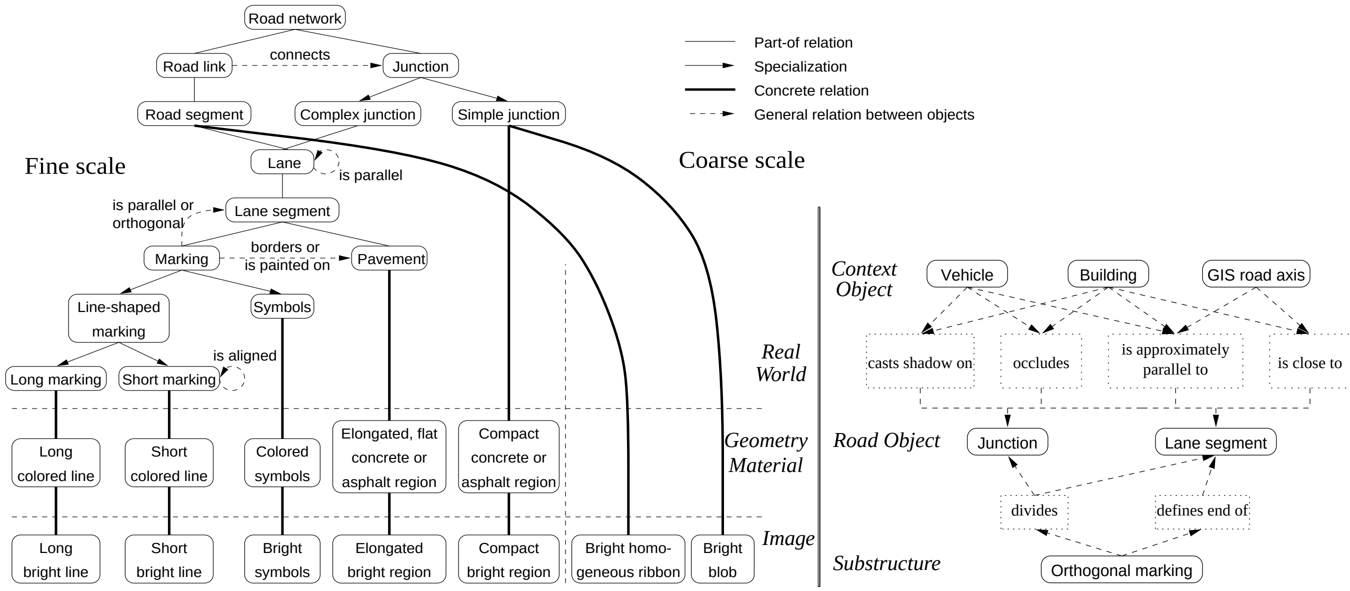


Figure 1: (a) Road model (left). (b) Context model (right).

similar way, we model the integration of GIS-axes and relations to sub-structures. Figure 1 b) summarizes the relations between road objects, context objects, and sub-structures by using the concepts ”Lane segment” and ”Junction” as the basic entities of a road network.

3.2 Extraction Strategy:

In a very general sense, the extraction strategy inheres knowledge about how and when certain parts of the road and context model are optimally exploited, thereby being the basic control mechanism of the extraction process. It is subdivided into three levels (see also Fig. 2): Context-based data analysis (Level 1) comprises the segmentation of the scene into the urban, rural, and forest area and the analysis of context relations. While road extraction in forest areas seems hardly possible without using additional sensors, e.g., infrared or LIDAR sensors, the extraction in rural areas may be performed with the system of (Baumgartner et al., 1999). In urban areas, extraction of salient roads (Level 2) includes the detection of homogeneous ribbons in coarse scale, collinear grouping thin bright lines, i.e. road markings, and the construction of lane segments from groups of road markings, road sides, and detected vehicles. The lane segments are further grouped into lanes, road segments, and roads. During road network completion (Level 3), finally, gaps in the extraction are iteratively closed by hypothesizing and verifying connections between previously extracted roads. Similar to (Wiedemann and Ebner, 2000), local as well as global criteria exploiting the network characteristics are used. Figure 3 illustrates some intermediate steps and Figs. 11, 12 show typical results. In the next section, we turn our focus on the integrated models for extraction and internal evaluation.

4 EXTRACTION AND EVALUATION MODELS

As (Tönjes et al., 1999) our approach utilizes a semantic net for modeling. However, our methodology of internal evaluation during extraction complements other work as we split the model of an object into components used for extraction and components used for internal evaluation. The model components used for extraction typically consist of quite generic geometric criteria which are more robust against illumination changes, shadows, noise, etc., whereas those used for evaluation are mostly object specific. In so doing, both extraction and evaluation may be performed in a flexible rather than monolithic fashion and can adapt to the respective contextual situation. The extraction of markings, for instance, is based on line detection while their evaluation relies on

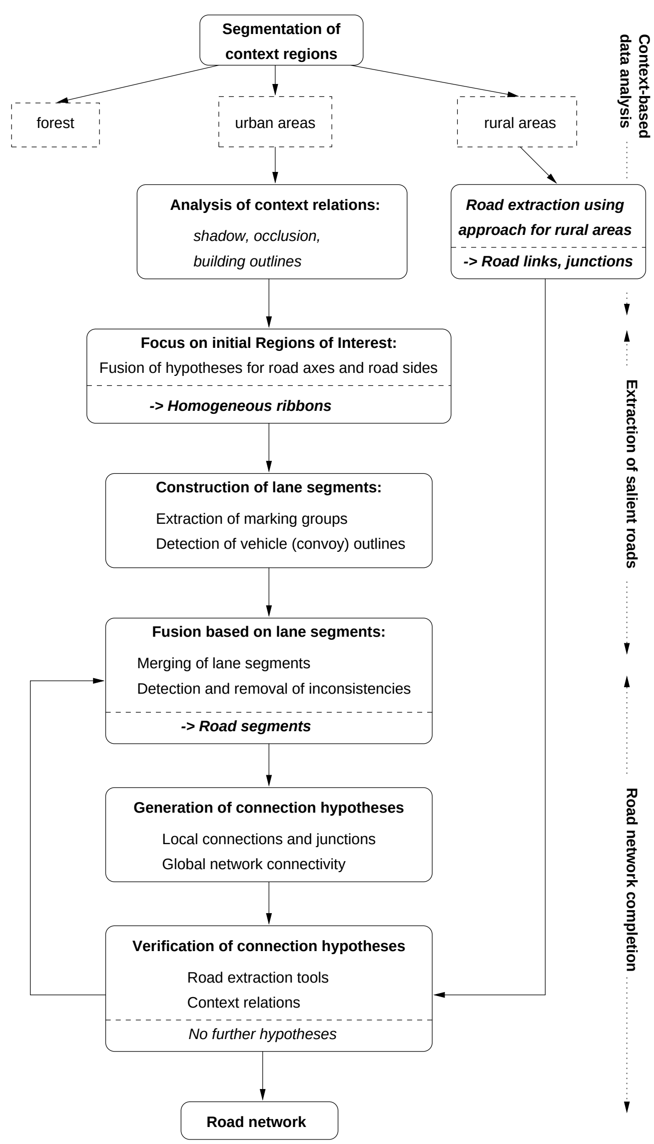
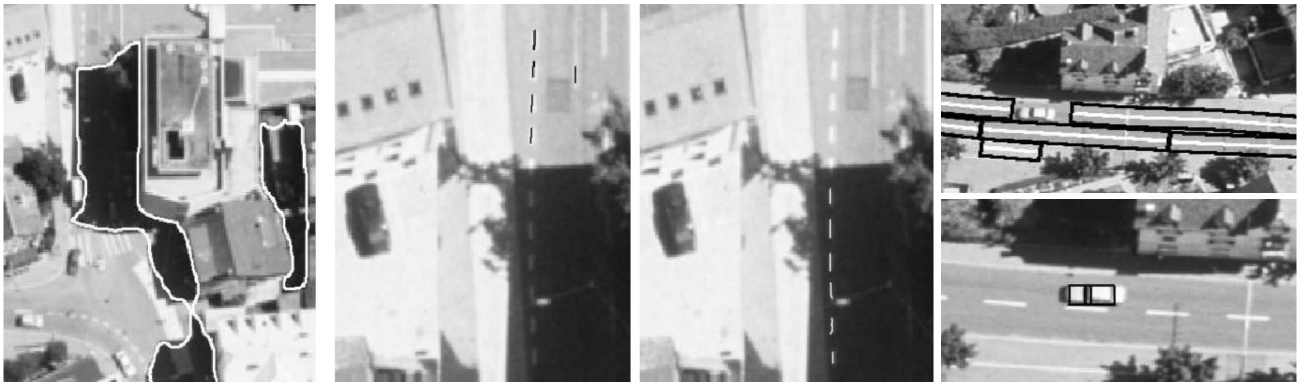


Figure 2: Extraction strategy for urban areas.



(a) Detected shadow areas (b) Markings outside of shadow area (c) Markings inside of shadow area (d) Verified lanes (top), detected car (bottom)

Figure 3: Examples of intermediate steps during road extraction

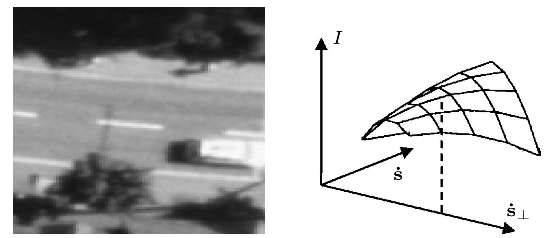
the knowledge that markings are very bright and have symmetric contrast on both sides because of the unicolored pavement (see Fig. 4). However, in case of shadow regions as detected during context-based data analysis, the system automatically retrieves a different parameter set for internal evaluation and, thus, accommodates the different situation.

In order to attain an unbiased evaluation, model components belonging to different types should be independent from each other. This is, of course, not always the case in practise. On one hand, we use the orientation difference between two markings as criterion for the extraction of groups of markings. On the other hand, the curvature of a group is part of the evaluation which is doubtless correlated with the orientation difference (see also Fig. 5). However, what makes a difference is the point of view on the object: In the first case only pairs of markings are considered. Therefore, the group may "wiggle" although yielding pairwise small orientation differences. In the second case the group is considered as a whole. Hence, notable wiggling would lead to a bad rating.

At each step of processing, internal evaluation is performed by not only aggregating previously derived values but also exploiting knowledge *not* used in prior steps. This point has especially high relevance for bottom-up driven image understanding systems (as ours), since essential global object properties making different objects distinctive can be exploited only at later stages of processing. Lanes segments, for instance, are constructed from grouped markings and optional road sides (Fig. 5, 7, 8), but they still have high similarity to, e.g., illuminated parts of gable roofs. Only their collinear and parallel concatenation resulting in lanes, road segments, and roads makes them distinctive and gives in turn new hints for missing lane segments (cf. Fig. 9, 10). Consider the two-lane road segment in Fig. 10a). The continuity of the upper lane provides a strong hint for bridging the gaps of the lower lane in spite of high intensity variation therein. Hence, at this stage, the system can base its decision on more knowledge than purely the homogeneity within the gaps.

Figures 4–10 summarize the employed extraction and evaluation models. Tables below the figures give detailed information about the respective model components and the expected values to measure (qualitatively). Linear features are denoted as smooth, unit-speed curve $s = s(l)$ neglecting the parameter l. Ribbons $s(w) = s(l, w)$ have an additional variable w parameterizing the ribbon profiles in direction of the unit normal vector $\dot{\mathbf{s}}_\perp$ (bold letters for vectors). I stands for grayvalue intensities and H are heights given by a Raster-DSM.

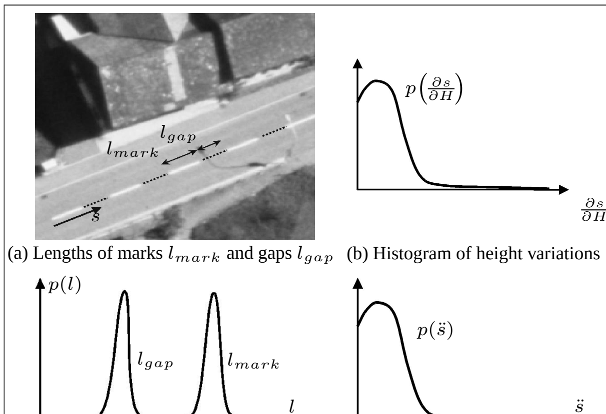
In the implementation, fuzzy-set theory is used for transforming knowledge as represented by the model into a mathematical framework. The internal evaluation of each object is based on fuzzy-functions which approximate the values to be extracted as they are expected by the model (illustrated by graphs in Figs. 4–10). Resulting confidence values are then combined by fuzzy-aggregation operations.



(a) Markings in aerial images (b) Line model (c) Asymmetry ΔI of line points (d) Typical intensities along marking

Figure 4: **Model for markings:**

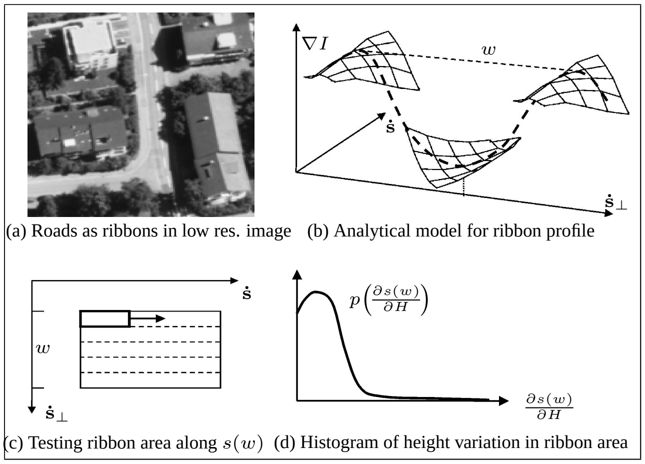
Components used for **extraction**	Components used for **evaluation**
▷ Intensity: Curvature maximum along $\dot{\mathbf{s}}_\perp$ ▷ Length of s: lower bound	▷ Asymmetry ΔI of parabolic profile along $\dot{\mathbf{s}}_\perp$: small ▷ Intensity along s: high



(a) Lengths of marks l_{mark} and gaps l_{gap} (b) Histogram of height variations (c) Histogram of lengths (d) Histogram of curvatures

Figure 5: **Model for grouped markings:**

Components used for **extraction**	Components for **evaluation**
▷ Orientation difference of pairs of markings and gaps: limited ▷ Gap length: limited ▷ Length of group: lower bound	▷ Lengths of markings and gaps: constant within group ▷ Overall curvature $\ddot{s}$: low ▷ Height variation of s: low

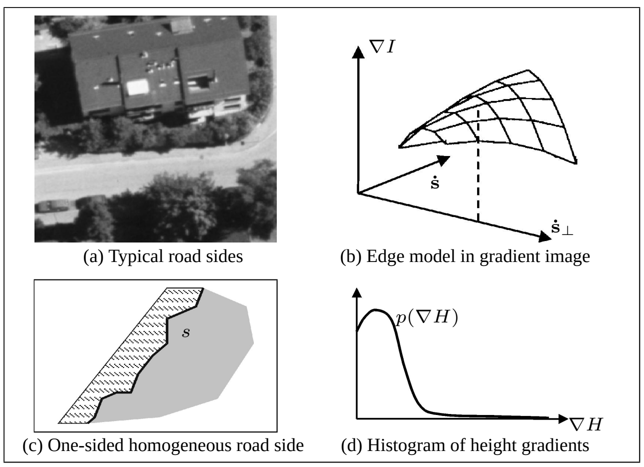


(a) Roads as ribbons in low res. image (b) Analytical model for ribbon profile

(c) Testing ribbon area along $s(w)$ (d) Histogram of height variation in ribbon area

Figure 6: **Model for ribbons:**

Components used for **extraction**	Components used for **evaluation**
▷ Profile of gradient ∇I along $\dot{\mathbf{s}}_\perp$: "half-pipe"	▷ Height variation of $s(w)$: low
▷ Width of ribbon w: bounded	▷ Intensity of $s(w)$: high
▷ Length of $s(w)$: lower bound	▷ Homogeneity of $s(w)$: distinct

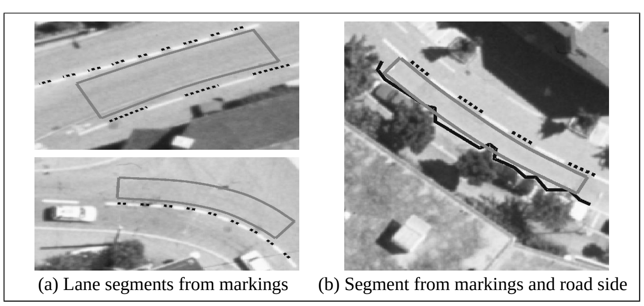


(a) Typical road sides (b) Edge model in gradient image

(c) One-sided homogeneous road side (d) Histogram of height gradients

Figure 7: **Model for road sides:**

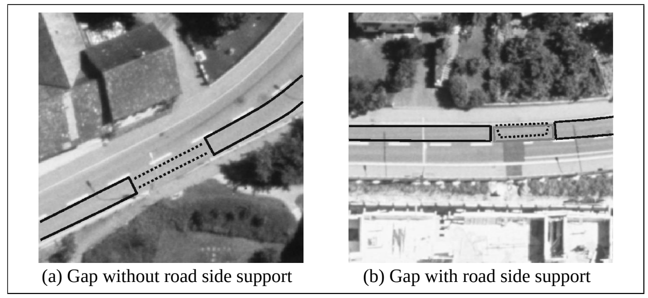
Components used for **extraction**	Components used for **evaluation**
▷ Gradient ∇I: curvature maximum along $\dot{\mathbf{s}}_\perp$	▷ Areas beside s: at least one homogeneous area required
▷ Length of s: lower bound	▷ Height gradient ∇H: low



(a) Lane segments from markings (b) Segment from markings and road side

Figure 8: **Model for lane segments:**

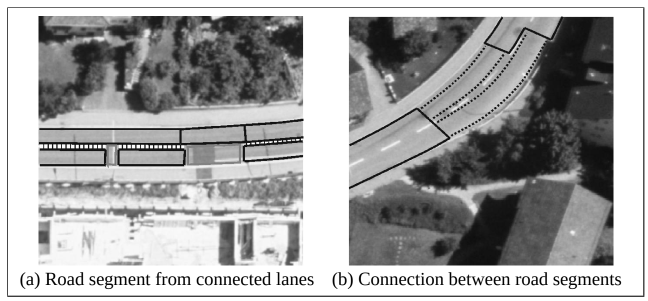
Components used for **extraction**	Components used for **evaluation**
▷ Groups of markings (pair): parallel, width bounded	▷ Intensity: bright (see illustration in Fig. 6 "Ribbons")
▷ Group of markings (isolated): width hypothesized	▷ Homogeneity: distinct (see illustration in Fig. 6 "Ribbons")
▷ Group of markings and road side: parallel, width bounded	▷ Height variation: low (see illustration in Fig. 6 "Ribbons")



(a) Gap without road side support (b) Gap with road side support

Figure 9: **Model for grouping lane segments into lanes:**

Components used for **extraction**	Components used for **evaluation**
▷ Orientation difference between pairs of lane segments: limited	▷ Gap analysis: see evaluation of lane segments
▷ Gap length: limited	▷ Support of road sides: high
▷ Lane segment widths: similar	▷ Overall curvature: low
▷ Lane segment heights: similar	▷ Overall height variation: low



(a) Road segment from connected lanes (b) Connection between road segments

Figure 10: **Model for road segments and road links:**

Components used for **extraction of road segments**	Components used for **evaluation of road segments**
▷ Parallelism of neighboring lanes: high	▷ Widths of lanes across road segments: similar
▷ Gap analysis *within* road segment: see evaluation of lanes	▷ Heights of neighboring lanes: similar
	▷ Fragmentation (missing lane segments): low

Components used for **extraction of road links**	Components used for **evaluation of road links**
▷ Orientation difference between pairs of road segments: limited	▷ Length of road link: high
▷ Gap length: limited	▷ Overall curvature: low
▷ Road segments to connect: compatible lane configuration	▷ Overall height variation: low
▷ Gap analysis: see extraction and evaluation of road segments	

5 RESULTS AND DISCUSSION

Figures 11 and 12 show the final result of road extraction. The results have been evaluated by matching the extracted road axes to manually plotted reference data (Wiedemann and Ebner, 2000). As can be seen, major parts of the road networks have been extracted (white lines indicate extracted road axes). Expressed in numerical values, we achieve a completeness of almost 70 % and a correctness of about 95 %. The system is able to detect shadowed road sections or road sections with rather dense traffic. However, it must be noted that some of the axes' underlying lane segments have been missed. This is most evident at the complex road junctions in both scenes, where only spurious features for the construction of lanes could be extracted. Thus, not enough

Figure 11: Extracted road network of Scene I

Figure 12: Extracted road network of Scene II

evidence was given to accept connections between the individual branches of the junction. Another obvious failure can be seen at the right branch of the junction in the central part of Scene II (Fig. 12). The tram and trucks in the center of the road have been missed since our vehicle detection module is only able to extract vehicles similar to passenger cars. Thus, this particular road axis has been shifted to the lower part of the road where the implemented parts of the model fit much better.

In summary, the results indicate that the presented system extracts roads even in complex environments. The robustness is last but not least a result of the detailed modelling of both extraction and evaluation components accommodating the mandatory flexibility of the extraction. An obvious deficiency exists in form of the missing detection capability for vehicle types as busses and trucks and the (still) weak model for complex junctions. The next extension of our system, however, is the incorporation of multiple overlapping images in order to accumulate more evidence for lanes and roads in such difficult cases. The internal evaluation will greatly contribute to this because different – possibly competing – extraction results have to be combined. Also for multiple images, we plan to treat the processing steps up to the generation of lanes purely as 2D-problem. The results for each image are then projected onto the DSM and fused there to achieve a consistent dataset. Then, new connections will be hypothesized and, again, verified in each image separately.

REFERENCES

Baltsavias, E., Gruen, A. and van Gool, L. (eds), 2001. Automatic Extraction of Man-Made Objects from Aerial and Space Images (III). Balkema Publishers, Lisse, The Netherlands.

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

Clément, V., Giraudon, G., Houzelle, S. and Sandakly, F., 1993. Interpretation of Remotely Sensed Images in a Context of Multisensor Fusion Using a Multispecialist Architecture. IEEE Transactions on Geoscience and Remote Sensing 31(4), pp. 779–791.

Faber, A. and Förstner, W., 2000. Detection of Dominant Orthogonal Structures in Small Scale Imagery. In: International Archives of Photogrammetry and Remote Sensing, Vol. 33, part B.

Förstner, W., 1996. 10 pros and cons against performance characterization of vision algorithms. In: H. I. Christensen, W. Förstner and C. B. Madsen (eds), Workshop on Performance Characteristics of Vision Algorithms, pp. 13–29.

Fuchs, C., Gülch, E. and Förstner, W., 1998. OEEPE Survey on 3D-City Models. OEEPE Publication, 35.

Gruen, A., Baltsavias, E. and Henricsson, O. (eds), 1997. Automatic Extraction of Man-Made Objects from Aerial and Space Images (II). Birkhäuser Verlag, Basel.

Gruen, A., Kuebler, O. and Agouris, P. (eds), 1995. Automatic Extraction of Man-Made Objects from Aerial and Space Images. Birkhäuser Verlag, Basel.

Heller, A., Fischler, M., Bolles, R. and Connolly, C., 1998. An Integrated Feasibility Demonstration for Automatic Population of Spatial Databases. In: Image Understanding Workshop '98.

Hinz, S. and Baumgartner, A., 2001. Vehicle Detection in Aerial Images Using Generic Features, Grouping, and Context. In: Pattern Recognition (DAGM 2001), Lecture Notes on Computer Science 2191, Springer-Verlag, pp. 45–52.

Hinz, S., Baumgartner, A. and Ebner, H., 2001a. Modelling Contextual Knowledge for Controlling Road Extraction in Urban Areas. In: IEEE/ISPRS joint Workshop on Remote Sensing and Data Fusion over Urban Areas.

Hinz, S., Baumgartner, A., Mayer, H., Wiedemann, C. and Ebner, H., 2001b. Road Extraction Focussing on Urban Areas. In: (Baltsavias et al., 2001), pp. 255–265.

Laptev, I., Mayer, H., Lindeberg, T., Eckstein, W., Steger, C. and Baumgartner, A., 2000. Automatic Extraction of Roads from Aerial Images Based on Scale Space and Snakes. Machine Vision and Applications 12(1), pp. 22–31.

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

Price, K., 2000. Urban Street Grid Description and Verification. In: 5th IEEE Workshop on Applications of Computer Vision, pp. 148–154.

Ruskoné, R., 1996. Road Network Automatic Extraction by Local Context Interpretation: application to the production of cartographic data. PhD thesis, Université Marne-La-Valleé.

Tönjes, R., Growe, S., Bückner, J. and Liedke, C.-E., 1999. Knowledge-Based Interpretation of Remote Sensing Images Using Semantic Nets. Photogrammetric Engineering and Remote Sensing 65(7), pp. 811–821.

Tupin, F., Bloch, I. and 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), pp. 1327–1343.

Wang, Y. and Trinder, J., 2000. Road Network Extraction by Hierarchical Grouping. In: International Archives of Photogrammetry and Remote Sensing, Vol. 33, part B.

Wiedemann, C. and Ebner, H., 2000. Automatic completion and evaluation of road networks. In: International Archives of Photogrammetry and Remote Sensing, Vol. 33, part B.

Zhang, C. and Baltsavias, E., 1999. Road Network Detection by Mathematical Morphology. In: International Workshop on 3D Geospatial Data Production: Meeting Application Requirements, Paris.