# The Role of Grouping for Road Extraction

**Carsten Steger, Helmut Mayer, Bernd Radig**

Forschungsgruppe Bildverstehen (FG BV), Informatik IX
Technische Universität München
Orleansstraße 34, 81667 München, Germany
Ph.: +49-89-48095-122, Fax: +49-89-48095-203
e-mail: {stegerc|radig}@informatik.tu-muenchen.de

Lehrstuhl für Photogrammetrie und Fernerkundung
Technische Universität München
Arcisstraße 21, 80290 München, Germany
Ph.: +49-89-289-22671, Fax: +49-89-280-9573
e-mail: helmut@photo.verm.tu-muenchen.de

**Abstract**

An approach to complete road networks extracted from aerial images is presented. Since low-level road extraction results will generally be fragmented and contain false hypotheses, this task involves selecting the correct roads from the extraction results as well as connecting them to construct the road network. Since the presented approach models the road network as a graph, it can handle different kinds of low-level representations, e.g., road segments given by lines or polygons. A flexible scheme to evaluate the quality of the connection hypotheses based on fuzzy set theory is introduced. The problem of connecting the road network is reduced to selecting a few salient nodes in the graph and finding an optimal path between them. Salient nodes are, for instance, the points where a road crosses the image border or points at the ends of very long road segments. Practical results show the validity of the approach.

## 1 Introduction

One of the major problems any image interpretation system, and in particular road extraction, has to deal with is that the results of the extraction of primitives will be incomplete. The reasons for this are manifold. Examples are failures of low-level operators like edge detectors, or the deviation of the appearance of real-world objects from the assumed model, e.g., occluded roads due to shadows. In order to overcome this problem, perceptual grouping algorithms are often used in image interpretation systems to extract meaningful entities from the segmentation results based on general organizational principles such as similarity, proximity, continuation, symmetry, and closure (Mohan and Nevatia 1992, Sarkar and Boyer 1993).

For road extraction the problem one has to deal with is that the extracted road network will generally be incomplete and fragmented. Therefore, the extracted road segments have to be grouped into a complete road network. The proposed schemes to solve this problem can be classified according to which kind of input data they use.

The first kind of algorithms uses the raw, pixel-based output of a feature detection algorithm, e.g., a line detector, as input. Fischler et al. (1981) determine a cost array for the entire image from the output of several low-level extraction schemes. The cost array contains a likelihood that a particular pixel belongs to a road. Then, optimal paths between two very likely road pixels are determined by the F* algorithm. The output of this step serves as a road hypothesis, which is deleted from the cost array, and the process is repeated with other likely road pixels to obtain additional road hypotheses. Merlet and Zerubia (1996) extend this approach to take into account neighborhoods of higher order. Thus they are able to measure the curvature of the extracted road segments as well. Optimal paths are computed by an extension of the F* algorithm. Both these approaches are similar to the snake-based approach of Montesinos and Alquier (1996), in which an evaluation of each pixel is calculated and propagated from neighboring pixels. To select salient roads, optimal paths from the pixels with the highest evaluation are traced. Finally, Fischler (1994) deals with the problem of extracting single linear structures where a certain percentage of points is missing in a noisy background. This is done by first eliminating most of the noise through an operation similar to a binary rank operator. Then, a neighborhood graph is constructed between pixels having a certain maximum distance, and the diameter path of the minimum spanning tree of this graph is extracted as the single salient line. In all these schemes conflicts do not pose a problem since optimal paths are extracted.

The second kind of input are segmentation results with enriched attributes, e.g., rectangular road segments. Consequently, the grouping is done on a symbolic level. Vasudevan et al. (1988) use the output of two low-level operators to obtain curvilinear segments. They do not address the problem of removing false road segments. The segments are grouped based on the distance between their nearest end points and their collinearity using hard thresholds. If conflicting hypotheses arise no decision is made. Zhu and Yeh (1986) use overlapping anti-parallel line segments as primitives. Salient road segments are selected based on their length and contrast. These are then extended by linking other segments within a rectangle of three times the road witdh around the end of the current road segment. Grouping candidates must have similar direction, width, and contrast. Furthermore, the search area is checked for additional road evidence using edge detection. Conflicts are resolved by using a rule-based system. Finally, Ruskoné et al. (1994) use rectangles as primitives to build up an incomplete road network graph. Linking hypotheses are generated and evaluated for road segments that are close, and collinear or perpendicular. The road network graph is also searched for the best connection of these two segments. The link is only added if its evaluation is significantly better than the best path in the graph.

This paper presents an approach to extract complete road networks which is relatively independent of the scale and representation of the low-level extraction results. Furthermore, an attempt is made to modularize the evaluation of the quality of a linking hypothesis, so that different or new criteria can be added to the algorithm easily. Finally, the problem of selecting and connecting the network is handled by well-known graph-theoretic algorithms.

# 2 Grouping Algorithm

## 2.1 Requirements for Grouping Roads

The roads which can be extracted from aerial or satellite images will generally be fragmented. This means that they do not comprise the complete road network, no matter how sophisticated the low-level extraction strategy is. Reasons for this are usually shadows cast onto the road by other objects, such as buildings or forests, or occlusions, for example due to trees, which are typically not contained in the low-level road model. Furthermore, other objects can exhibit the same characteristics that the road model assumes, e.g., roofs of houses. Therefore, the segmentation will usually also contain several false road hypotheses.

The goal of grouping road segments is therefore twofold. First of all, the extracted road segments should be aggregated as far as possible into a topologically complete road network. This implies that salient linear structures belonging to the road network should be selected and connected by the grouping algorithm. Secondly, this also implies that linear structures not belonging to the network should be rejected, i.e., not connected to the road network. Therefore, the algorithm must be very selective in which segments it adds to the road network.

Many of the grouping algorithms presented in Sect. 1 are based on connecting all road segments in every feasible combination using purely local criteria, e.g., distance and collinearity, and hard thresholds. The problem with this approach is that often it is nearly impossible to decide locally which segments should be joined. Fig. 1 illustrates a typical situation which might occur in practice. Let us assume that the upper middle road segment is a false positive. A typical grouping algorithm would either generate two connection hypotheses from A to B or none at all. The result is either an overly connected road network or a disconnected one.

In contrast, the main property of the road network in the real world is to connect certain places with each other, so that human beings can get from one place to another. Therefore, the deciding criterion whether to link two road segments is whether the proposed link will allow us to travel between certain places, i.e., a link should only be added if it allows us to get from point A to point B. Usually, there will be only one good connection between such places since the road network is optimized to get from A to B quickly or conveniently (Ruskoné et al. 1994). Therefore, whether two segments should be joined depends on the topology of the entire road network, i.e., connectivity is the important criterion, and not only whether two road segments fit together locally.

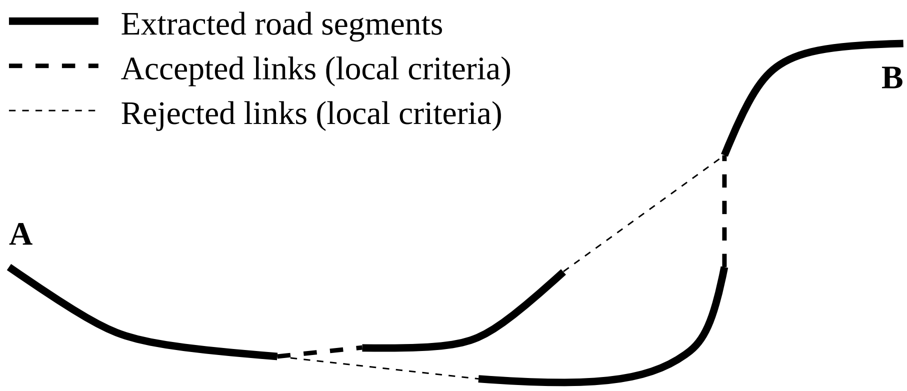



**Fig. 1:** Possible problems encountered when road segments are linked using purely local criteria and hard thresholds only.

These criteria lead to the following requirements for the grouping algorithm: First of all, hard decisions should be avoided where possible. Instead, local links should only be evaluated by some quality measure that takes on values in a certain kind of range, e.g., in $[0, 1]$. Then, based on the connectivity property, the algorithm should try to find an optimal path between each two of a set of "important" places in the road network in order to decide which segments to link. Which places are important will be discussed below. Basically, important places should be selected according to the probability with which they belong to the road network. The result of the algorithm is then a road network of several connected components, containing very probable road segments and links.

## 2.2 Evaluation of Road Segments and Links

Before the evaluation procedure for the links can be developed it must be clear what parts a road network consists of. The most natural representation for the network is a graph in which the junctions and end points of the road segments are the vertices and the road segments are the edges (Ruskoné et al. 1994, Moissinac et al. 1995). This representation is valid for all resolution levels, and it has the advantage that the primitive constituents, i.e., road segments and junctions, can be extracted in several resolutions (Steger 1996a, Steger 1996b, Baumgartner et al. 1997b).

With this data structure, the elements which should be evaluated for their compatibility are obviously the vertices in the graph. The goal then is to use various criteria to test whether two vertices might be connected, each of which should avoid hard thresholds, and each of which should have a semantics which is easy to understand. However, it is important that this evaluation is not done in one single, monolithic procedure. It should rather be done in a modularized fashion, so that new criteria can be added easily, and even automatically if certain kinds of data, e.g., a digital surface model (DSM), are available for a data set. Therefore, a flexible scheme to combine various evidences is needed.

Because of these requirements, fuzzy set theory (Mendel 1995) was chosen as the basic means to evaluate the quality of a link. It closely models the way a human would approach the problem. For instance, the notion of closeness of two vertices is a typical fuzzy variable for humans since we can be sure that two vertices are close to each other (fuzzy value 1) if they are less than 20 m apart, while they surely are not close (fuzzy value 0) if they are more than 100 m apart, for example. In between these values the notion of closeness drops from 1 to 0. A fuzzy function is an ideal means to model this notion (Mendel 1995). Furthermore, fuzzy set theory has the advantage that different evidences can be combined easily by means of the fuzzy *and*, *or*, and *not* operations, thus facilitating modularization of the criteria.

Thus, we can define a fuzzy relation over the vertices $V$

$$R(V,V) = \{((v_i, v_j), \mu_R(v_i, v_j)) \mid (v_i, v_j) \in V \times V\} \ , \tag{1}$$

where $\mu_R(v_i, v_j)$ is a fuzzy function describing the quality of a link between two vertices in the graph, i.e., each individual link is assigned a fuzzy value $r_{i,j} = \mu_R(v_i, v_j) \in [0, 1]$. As noted above, $\mu_R(v_i, v_j)$ may be a combination of several criteria, e.g., absolute distance ($A$), relative distance ($B$), and collinearity ($C$), which may simply be written as $\mu_R(v_i, v_j) = \mu_A(v_i, v_j) \wedge \mu_B(v_i, v_j) \wedge \mu_C(v_i, v_j)$, where $\wedge$ denotes the fuzzy *and* operation.

With this fuzzy relation it is possible to construct a weighted graph which will be used to generate linking hypotheses, and thus to extract the road network. The basic idea is to find the shortest paths in the weighted graph with suitably chosen distances, as described in Sect. 2.3. Therefore, the weights in the graph should somehow reflect the true distances in the road network, but depending on how a link is evaluated, the distance between two vertices should be increased to make it harder to bridge obviously bad gaps. If a link is considered perfect, i.e., has the fuzzy value 1, the true distance between the vertices is used. If the link has the fuzzy value 0, its weight must be $\infty$. Therefore, the following formula is used to construct the weighted graph:

$$w_{i,j} = \begin{cases} l_{i,j}/r_{i,j} & \text{if vertices } i \text{ and } j \text{ are connected by a road segment of} \\ & \text{length } l_{i,j} \text{ and } r_{i,j} > 0 \\ d_{i,j}/r_{i,j} & \text{if } i \text{ and } j \text{ are not connected in the original graph, but } r_{i,j} > 0 \\ & (d_{i,j} \text{ is the distance between vertices } i \text{ and } j) \\ \infty & \text{otherwise (i.e., no edge in the graph)} \end{cases} \tag{2}$$

where $w_{i,j}$ is the weight of the edge between the vertices $i$ and $j$.

### 2.3 Extraction of the Road Network

As discussed in Sect. 2.1, the selection of the road network relies on the selection of “important” places, i.e., vertices, in the graph, which are then connected. Which vertices in the graph are important strongly depends on the likelihood that the road segment this vertex belongs to is a true road segment, and not a false positive. Since we assume that the road segments are extracted by low-level methods, the segments will usually not carry a reliable internal quality measure that could be used to assess this likelihood, and therefore heuristics have to be used to measure it. Since the road network eventually has to cross the image border, a very simple, but surprisingly effective, heuristic is to select all vertices lying close to the image border. More sophisticated schemes might take into account the length of the extracted road segments, and select vertices at the end of very long segments, e.g., longer than 50 m. An even more sophisticated scheme would be to use knowledge on where the low-level extraction scheme provides good and stable results, and to use vertices in these context regions as starting points. For example, road extraction is usually most stable in open rural areas (Baumgartner et al. 1997b), and thus the road hypotheses there are good starting points. One could even use a combination of all these schemes.

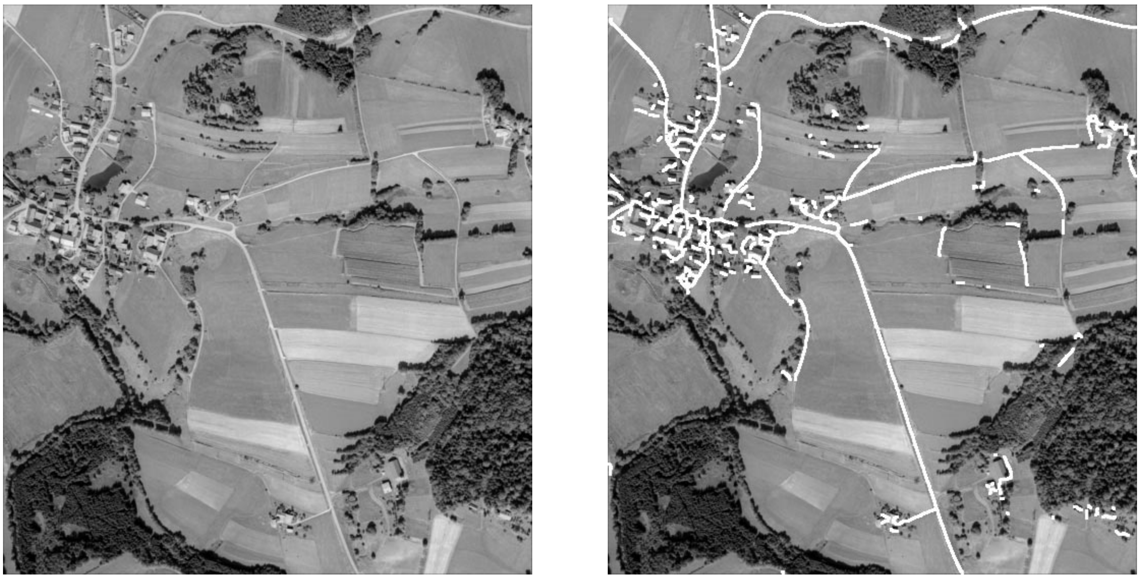
After the selection of the important vertices of the graph, they are connected by searching for the shortest path between each pair of the selected vertices using the Dijkstra algorithm (Knuth 1994). The final road network then consists of all vertices and edges lying on any of the selected paths.

It should be noted that the network thus created may contain false connection hypotheses. Therefore, the found connection hypotheses should be validated whenever possible, e.g., if the road network was extracted in a low resolution image, but a high resolution image containing the details of the same area is available as well. The context sketches described in (Baumgartner et al. 1997a) can give valuable hints on possible reasons for the incomplete extraction of the road network. For example, if a shadow is the reason for a missing road segment, the snake-based approach given in (Baumgartner et al. 1997a) can be used to extract possible weak roadsides from the image, and to judge their quality based on their geometry, e.g., their straightness and curvature. If a connection hypotheses is rejected by the validation step, its corresponding edge can be deleted from the weighted graph, and thus the next best connections can be found by again searching for optimal paths in the graph.

## 3 Results

This section presents results obtainable with the proposed approach. Fig. 2a) shows an aerial image with a ground resolution of 2 m. The line extraction algorithm described in (Steger 1996b) is used to extract road segments. Of course, the scheme described in (Baumgartner et al. 1997b), which extracts road segments as closed polygons, may be used as well. As can be seen from Fig. 2b), the algorithm extracts most of the true roads in the image, but also many roofs of buildings and a few fields.

From these segmentation results an initial, unweighted graph is constructed. Then the algorithm described in Sect. 2.2 is used to evaluate the quality of the links between the vertices. The first criterion used is a measure of absolute distance of the vertices, i.e., vertices closer than 20 m get the fuzzy value 1, vertices farther than 100 m get the fuzzy value 0, and all other values are interpolated linearly. As a second criterion, the relative distance of the vertices is used, i.e., the distance of the vertices is compared against the length of shorter one of the longest road segment ending in each of the two vertices. If the ratio of the length of the gap to the length of the road segment is smaller than 1 its evaluation is set to 1, while if the ratio is larger than 3 the evaluation is 0. The last criterion is a measure of collinearity of the road segments ending in the respective vertices. This



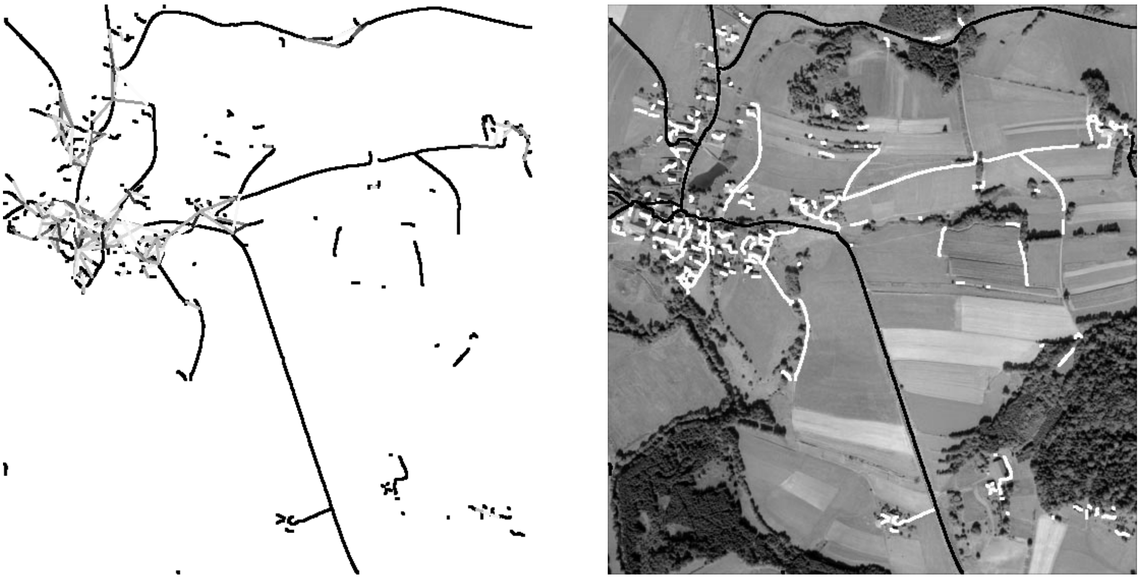
a) b)

**Fig. 2:** a) Aerial image with ground resolution of 2 m b) Detected lines

measure is defined by the maximum of the two angles formed by the line connecting the two vertices and the direction of the road segment at each vertex. If more than one road segment ends in any vertex, the smallest angle at that vertex is used. Angles smaller than $20^\circ$ get the evaluation 1, while angles larger than $60^\circ$ are evaluated with 0. As can be seen, the criteria are very liberal in order to avoid hard decisions. All these criteria are combined using the fuzzy *and* operator. Fig. 3a) visualizes the result of the evaluation procedure. Edges of the graph displayed in black have the fuzzy evaluation 1, while lighter edges have a correspondingly smaller fuzzy value. Please note that all edges that are connected by road segments have the perfect evaluation 1. One could also use measures on these links, e.g., whether they are smooth enough to be road segments (Zlotnick and Carnine, Jr. 1993), in order to obtain better results.

Fig. 3b) shows the selected and connected road network extracted from the weighted graph obtained from this fuzzy relation. In this case, the selected vertices were the ones adjacent to the image border. As can be seen, the algorithm was able to extract the main road network. The most prominent failure is the missing connection of the road in the right center to the right image border. This is because there is a gap in which the road directions are almost parallel due to the shadow of a tree, so that neither a vertex in the graph was extracted, nor a link could be hypothesized. Furthermore, the dead end roads were not connected to the network since their corresponding vertices were not selected.

While the road network extracted with the above criteria is quite good, a few of the selected links lead right over the roofs of some houses, most notably for the road starting at the upper left corner of the image. These errors can be avoided if a DSM is available for the scene. A fourth criterion was used to evaluate the links and road segments in the graph. It measures the flatness of the road by using the maximum gradient on the road,



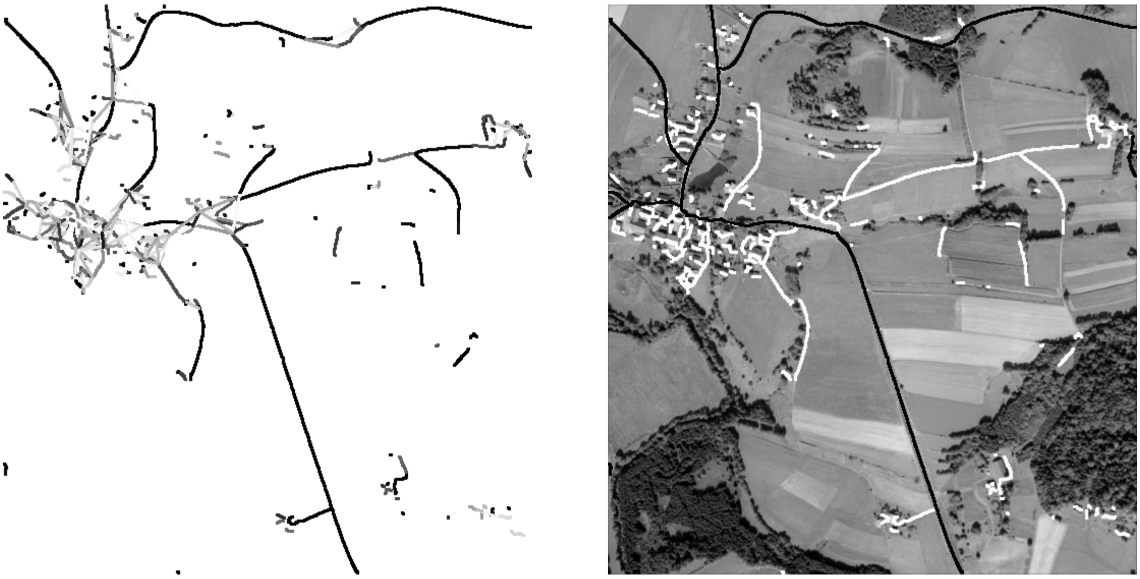
a) b)

**Fig. 3:** a) Fuzzy evaluation of road segments and links b) Selected road network (black)

as extracted from the DSM, and was added to the first three criteria by again using the fuzzy *and*. Fig. 4a) shows the result after the evaluation of the links using these four criteria. Please note that now also the original road segments have fuzzy evaluations smaller than 1. Fig. 4b) shows the extracted road network. As can be seen, the road in the upper left corner of the image now is correctly connected. Thus, an aerial image interpretation system using this grouping scheme can adapt itself very easily to the available data by simply adding new criteria to the linking stage.

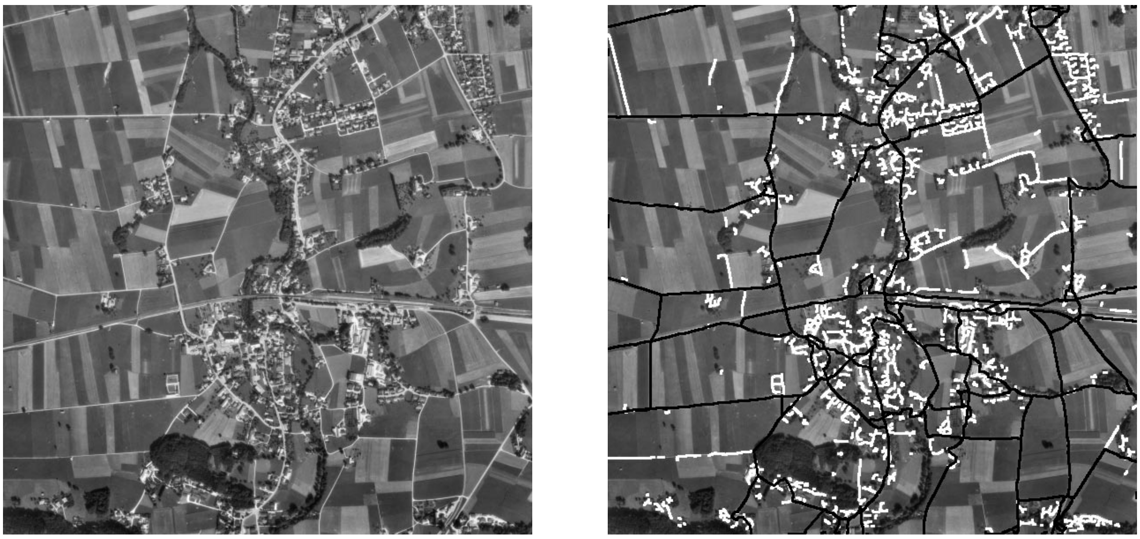
Fig. 5a) gives another example of the results obtainable with the proposed approach. It shows an aerial image of a ground resolution of 3.6 m containing a rural area with two villages. Fig. 5b) displays the extracted road network in black and the remaining line segments in white. As can be seen, the main road network is extracted correctly. As in the previous example, dead end streets and city block structures (cycles in the graph) in the residential areas of the two villages were not extracted. Furthermore, some connections could not be made due to the fact that the line extraction algorithm failed to extract some junctions, and thus some vertices. Since no new vertices are generated by the linking algorithm, problems like these cannot be overcome.

Finally, Fig. 6 demonstrates that the proposed algorithm may be used for a different kind of grouping. Fig. 6a) displays an image in which roads can only be recognized by their road markings because the roadsides exhibit no visible edges. Therefore, the road markings were extracted as bright lines with the algorithm given in (Steger 1996b). In order to extract roads it is necessary to extract the collinear road markings. Fig. 6b) shows the result of connecting manually selected points with optimal paths through the graph. The used criteria were the same as in the two previous examples, only adapted to the different resolutions. As can be seen, the algorithm is very successful in grouping the collinear



a) b)

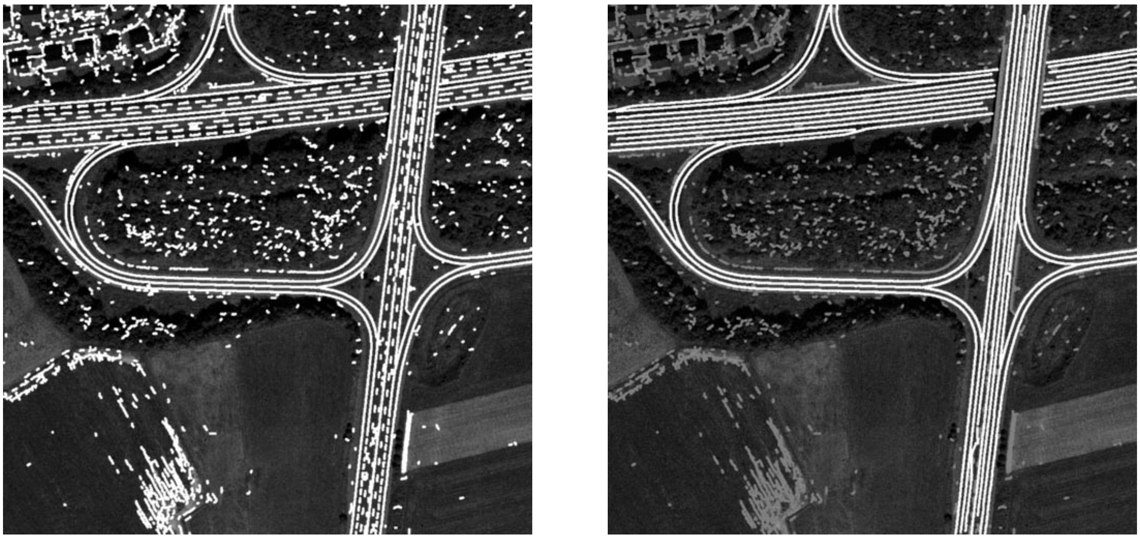
**Fig. 4:** a) Fuzzy evaluation of road segments and links, additionally using a DSM b) Selected road network (black)



a) b)

**Fig. 5:** a) Aerial image b) Selected road network (black)

road markings. To extract these automatically, only the graph search strategy would have to be adapted. A best-first search from a few salient road markings could be used. This strategy would try to add the road marking with the best connection evaluation first. Since it is possible that lanes could be switched by this procedure, e.g., if the directions of the road markings were not extracted perfectly, a global evaluation step would have to follow



a) b)

**Fig. 6:** a) Aerial image with extracted lines b) Selected road markings (white)

each try to add a new road marking. This evaluation should take into account the global collinearity of the grouped lines. The search stops when there are no more markings to add, or if the best added marking spoils the global collinearity too much. After the extraction of the collinear road markings they can be grouped to road hypotheses by finding, possibly multiple, parallel markings using an approach similar to the one given in (Steger et al. 1995).

## 4 Conclusions

This paper has presented the role of grouping for the completion of road networks from aerial images. The proposed approach uses a graph representation of the road network, which allows the use of different kinds of low-level segmentation results. Thus, the linking problem can be related to the evaluation of the compatibility of two vertices in this graph. Therefore, a general and flexible scheme to evaluate these links between road segments was proposed, which uses intuitively selectable fuzzy functions. Connection hypotheses are extracted by searching for optimal paths between salient vertices in the graph. Thus, competing hypotheses are eliminated. Furthermore, the problem of selecting road segments belonging to the road network is reduced to the selection of only a few important vertices in the graph, for which several heuristics were proposed. Finally, it was shown that the algorithm can also be used for other applications, e.g., grouping of collinear road markings. Only the graph search strategy needs to be changed, since there the problem of selecting salient points to connect is very hard to solve for this kind of problem.

The main limitation of the algorithm is that it assumes that junctions in the road network, i.e., vertices in the graph, will be completely extracted by the low level algorithm. Therefore, if a T-junction is missed, it will not be connected to the road network, since there is no corresponding vertex in the graph to form a link. This could be avoided by adding some junctions in places where almost perpendicular links could be suspected, and adding an evaluation function that gives a high evaluation to this configuration. Furthermore, in some cases it might be advantageous to insert vertices in areas of high curvature. However, care must be taken to label these vertices specially, since the evaluation should give a high score only at vertices that were inserted to allow for this type of connection. Further research will focus on these topics.

## Acknowledgements

This work was funded by the Deutsche Forschungsgemeinschaft (DFG) under grant no. Eb 74–8/2.

## References

Baumgartner A., C. Steger, H. Mayer, C. Heipke, H. Ebner (1997a) *Context-supported road extraction*, in A. Gruen, E. Baltsavias, O. Henricsson (eds), Automatic Extraction of Man-Made Objects from Aerial and Space Images (II), Birkhäuser Verlag, Basel, Switzerland.

Baumgartner A., C. Steger, H. Mayer, W. Eckstein (1997b) *Multi-resolution, semantic objects, and context for road extraction*, Workshop on Semantic Modeling for the Acquisition of Topographic Information from Images and Maps, Bonn, May 21–23, 1997.

Fischler M. A. (1994) *The perception of linear structure: A generic linker*, Image Understanding Workshop, Morgan Kaufmann Publishers, San Francisco, CA, USA, pp. 1565–1579.

Fischler M. A., J. M. Tenenbaum, H. C. Wolf (1981) *Detection of roads and linear structures in low-resolution aerial imagery using a multisource knowledge integration technique*, Computer Graphics and Image Processing, Vol. 15, pp. 201–223.

Knuth D. E. (1994) *The Stanford GraphBase: A Platform for Combinatorial Computing*, Addison-Wesley Publishing Company, Reading, MA, USA.

Mendel J. M. (1995) *Fuzzy logic systems for engineering: A tutorial*, Proceedings of the IEEE, Vol. 83, No. 3, pp. 345–377.

Merlet N., J. Zerubia (1996) *New prospects in line detection by dynamic programming*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 18, No. 4, pp. 426–431.

Mohan R., R. Nevatia (1992) *Perceptual organization for scene segmentation and description*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 14, No. 6, pp. 616–635.

Moissinac H., H. Maître, I. Bloch (1995) *Graph based urban scene analysis using symbolic data*, in D. M. McKeown Jr., I. J. Dowman (eds), Integrating Photogrammetric Techniques with Scene Analysis and Machine Vision II, Proc. SPIE 2486, pp. 93–104.

Montesinos P., L. Alquier (1996) *Perceptual organization of thin networks with active contour functions applied to medical and aerial images*, 13th International Conference on Pattern Recognition, Vol. I, IEEE Computer Society Press, pp. 647–651.

Ruskoné R., S. Airault, O. Jamet (1994) *Road network interpretation: A topological hypothesis driven system*, International Archives of Photogrammetry and Remote Sensing, Vol. XXX, part 3/2, pp. 711–717.

Sarkar S., K. L. Boyer (1993) *Integration, inference, and management of spatial information using bayesian networks: Perceptual organization*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 15, No. 3, pp. 256–274.

Steger C. (1996a) *Extracting curvilinear structures: A differential geometric approach*, in B. Buxton, R. Cipolla (eds), Fourth European Conference on Computer Vision, Vol. 1064 of Lecture Notes in Computer Science, Springer-Verlag, pp. 630–641.

Steger C. (1996b) *An unbiased detector of curvilinear structures*, Technical Report FGBV–96–03, Forschungsgruppe Bildverstehen (FG BV), Informatik IX, Technische Universität München.

Steger C., C. Glock, W. Eckstein, H. Mayer, B. Radig (1995) *Model-based road extraction from images*, in A. Gruen, O. Kuebler, P. Agouris (eds), Automatic Extraction of Man-Made Objects from Aerial and Space Images, Birkhäuser Verlag, Basel, Switzerland, pp. 275–284.

Vasudevan S., R. L. Cannon, J. C. Bezdek (1988) *Heuristics for intermediate level road finding algorithms*, Computer Vision, Graphics, and Image Processing, Vol. 44, pp. 175–190.

Zhu M.-L., P.-S. Yeh (1986) *Automatic road network detection on aerial photographs*, Computer Vision and Pattern Recognition, IEEE Computer Society Press, pp. 34–40.

Zlotnick A., P. Carnine, Jr. (1993) *Finding road seeds in aerial images*, Computer Vision, Graphics, and Image Processing: Image Understanding, Vol. 57, No. 2, pp. 243–260.