EXTERNAL EVALUATION OF ROAD NETWORKS

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ABSTRACT

Internal self-diagnosis and external evaluation of the obtained results are of major importance for the relevance of any automatic system for practical applications. Obviously, this statement is also true for automatic image analysis in photogrammetry and remote sensing. Recently, automatic systems for the extraction of road networks reached a state in which a systematic evaluation of the results seems to be meaningful.

This paper deals with the external evaluation of automatic road extraction results by comparison to manually plotted linear road axes used as reference data. The comparison is performed in two steps: (1) Matching of the extracted primitives to the reference network; (2) Calculation of quality measures. Each step depends on the other: the less tolerant is matching, the less exhaustive the extraction is considered to be, but the more accurate it looks. Therefore, matching is an important part of the evaluation process. The quality measures described in this paper comprise measures for the evaluation of the road axes, the network properties, and the crossings. The evaluation methodology is described in detail. Results for the evaluation of simulated as well as real data are presented and discussed. They show the behavior of the quality measures with respect to different deficiencies of the extraction results.

1 INTRODUCTION

Internal self-diagnosis and external evaluation of the obtained results are of major importance for the relevance of automatic systems for practical applications. Obviously, this statement is also true for automatic image analysis in photogrammetry and remote sensing. Recently, automatic systems reached a state in which a systematic evaluation of the results seems to be meaningful.

Both, internal self-diagnosis and external evaluation should yield quantitative results which are independent of a human observer. A good description for the result of internal self-diagnosis is the traffic light paradigm (Förstner, 1996): a green light stands for a result found to be correct as far as the diagnosis tool is concerned, a red light means an incorrect result, and a yellow light implies that further probing is necessary. External evaluation needs some kind of reference data and compares them to the automatically obtained results. In this paper we deal with the external evaluation of automatically extracted roads by means of comparison to manually plotted linear road axes used as reference data.

Some approaches on the evaluation of image analysis results can be found in the literature. In (McGlone and Shufelt, 1994) and (Hsieh, 1995) the evaluation of automated building extraction is reported. The results of the extraction are pixels (in image space) or voxels (in object space) which are classified as “building” or “non-building”. The degree of overlap between the results of the automated extraction and a manually generated reference is determined by matching of the corresponding pixels or voxels, respectively. Subsequently, measures for quantifying completeness and correctness of the extraction result are calculated. Road data from maps are analyzed with regard to distortions which are induced by the map production process in (Guérin et al., 1995). A data set of the French Topographic Database (BDTopo) is used as reference. The comparison is performed manually. The accuracy of the position of crossroads as well as the orientation of the connected roads, and their number and nature are investigated. Evaluation of the roads concentrates on measures for their geometrical accuracy. In (Airault et al., 1996) an evaluation methodology is proposed which is supposed to quantify the benefits of automatic and semi-automatic road extraction algorithms compared to manual data capture. The measures comprise geometric accuracy, success rate and in particular the time needed for data capture. (Ruskoné and Airault, 1997) present the evaluation of a multi-phase automatic road extraction. It points out the benefits of the different phases and quantifies the quality of the overall results. The reference data used is a data set of the BDTopo. Measures are geometric accuracy as well as exhaustivity of the extracted data. In (CMU, 1997, Harvey, 1999) the evaluation is directed towards measuring the quality of (semi-)automatic road extraction with different levels of manual intervention. The reference data is generated by a procedure starting at manually selected positions, followed by automatic road tracking and manual editing. Roads are extracted as regions, and matching of the extracted data with the reference data is carried out using an intersection operation. Only the exhaustivity of the extracted data is further considered. (Fua, 1997) evaluates the effectiveness of different methods for the initialization of ribbon snakes as well as the geometric accuracy of the extracted road data. Manually generated road data serve as reference data. The evaluation focuses on the amount of effort needed by an operator which is measured by the number of necessary mouse actions. Measures for the geometric accuracy of the extracted road data are average and maximum deviation from the reference data. In (Goodchild and Hunter, 1997), the matching of extraction and reference data is carried out using standard GIS functions. From the matching results, measures for the completeness and the correctness of the extraction results are calculated.

In Webster’s Dictionary (Webster’s, 1913), a road is defined as follows:

> A road is “a place where one may ride; an open way or public passage for vehicles, persons, and animals; a track for travel, forming a means of communication between one city, town, or place and another”

This definition is stamped by functional descriptions, especially the property of roads to form a mean of communication between different places. Outside of urban areas, the main function of roads is to provide connections for the transport of persons and goods as efficiently as possible (Pietzsch, 1989). Therefore, for an evaluation of road extraction results, it is not only important to take care of completeness and correctness, but also to evaluate the network properties.

This paper proposes and investigates a scheme for the evaluation of automatic road extraction. In this scheme various quality measures proposed in the literature are fused in a consistent manner. In addition, measures for the evaluation of the network properties are proposed.

In the next Section the evaluation methodology is described in detail. In section 3, results for the evaluation of simulated as well as real data are presented and discussed. The paper concludes with some final remarks and an outlook.

2 EVALUATION METHODOLOGY

The evaluation of the extracted road data is carried out by comparing the automatically extracted road centerlines with reference data. Both data sets are given in vector representation. The evaluation is processed in two steps: (1) Matching of the extracted road primitives to the reference network and (2) Calculation of quality measures.

Each step depends on the other: the less tolerant is matching, the less exhaustive the extraction is considered to be, but the more accurate it looks. Therefore, matching is an important part of the evaluation process.

2.1 Matching

The purpose of matching is twofold: Firstly, it yields those parts of the extracted data which are supposed to be roads, i.e., which correspond to the reference road data. Secondly, it shows which parts of the reference data are explained by the extracted data, i.e., which correspond to the extracted road data.

There are various ways to perform the actual matching of two networks. Especially if the geometric distortions are large and not known beforehand, relational matching was used successfully (Vosselman and Haala, 1992, Christmas et al., 1995). Special issues arise from the fact that the topologies of the reference and the extracted network can be different, and that the extraction can be redundant, i.e., extracted pieces overlap each other. The so called “buffer method”, is a simple matching procedure in which every portion of one network within a given distance from the other network is considered as matched. The matching is not affected by different network topologies. The drawbacks of this procedure are that a highly redundant extraction will not be detected and that direction differences between parts of the two networks are not taken into account. Yet another method for matching consists in searching for a unique, i.e., bijective correspondence between the two networks. Such attempts have been made (Walter, 1996), however, it is not clear how to define such a correspondence for topologically different networks on a general basis.

In our case, position and orientation of the road data to be matched is known. As a consequence, matching is performed according to the buffer method and additional attention is paid to the problem of redundancy and direction differences.

2.1.1 Buffer method in consideration of direction differences The principle of the buffer method in consideration of direction differences is that all parts of one data set, e.g., the extraction, which are close enough to parts of the other data set, e.g., the reference, are considered as matched if the direction difference between the respective parts of the two networks is small enough. In the following, this is described in two seperate steps:

In the first step, a buffer of constant predefined width (buffer width) is constructed around the reference (Fig. 1a). The parts of the extraction within the buffer are considered as matched if their direction difference to the respective parts of the reference does not exceed a given threshold.

In the second step matching is performed the other way round. The buffer is now constructed around the extraction (Fig. 1b), and the parts of the reference lying in the buffer and fulfilling the direction constraint are considered as matched.

2.1.2 Implementation Both, extraction and reference are assumed to be given as vector data. First of all, all nodes, which have a degree of two are eliminated. Then, equally spaced auxiliary nodes are inserted well directed along the edges of each network. From each node of each network, the shortest distance to the respective other network is determined under consideration of the direction difference. If this distance is smaller than the buffer width, the node is considered as *matched*, otherwise as *not matched*. As the distance s between the auxiliary nodes is known, the length of the matched/unmatched parts of the networks can be approximated by s times the number of matched/unmatched nodes. For the evaluation of the network, for each matched node, the foot of its perpendicular to the respective other network is stored and referred to as its homologous node in the following.

2.2 Evaluation of roads

In this section, the definitions of the quality measures are presented.

- $completeness = \frac{\textit{length of matched reference}}{\textit{length of reference}}$

  $\approx \frac{\textit{number of matched nodes of reference}}{\textit{number of nodes of reference}}$

  $completeness \in [0; 1]$

  The completeness is the percentage of the reference data which is explained by the extracted data, i.e., the percentage of the reference network which could be extracted.
  The optimum value for the completeness is 1.

- $correctness = \frac{\textit{length of matched extraction}}{\textit{length of extraction}}$

  $\approx \frac{\textit{number of matched nodes of extraction}}{\textit{number of nodes of extraction}}$

  $correctness \in [0; 1]$

  The correctness represents the percentage of correctly extracted road data, i.e., the percentage of the extraction, which is in accordance with the reference.
  The optimum value for the correctness is 1.

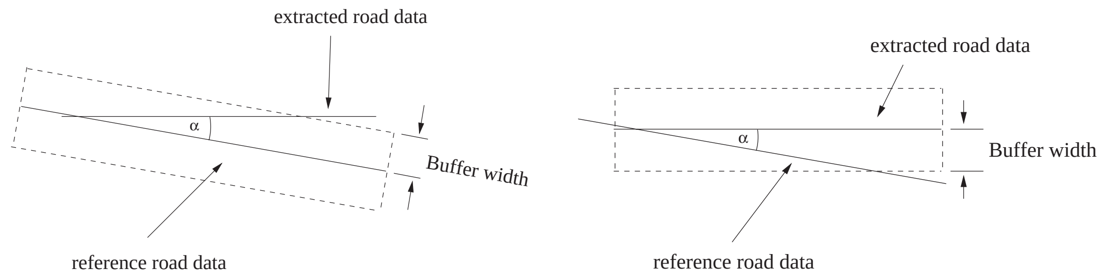
- $redundancy$

  $= \frac{\textit{length of matched extr. - length of matched ref.}}{\textit{length of matched extraction}}$

  $\approx \frac{\textit{\# matched nodes of extr. - \# matched nodes of ref.}}{\textit{number of nodes of extraction}}$

  $redundancy \in]-\infty; 1]$

  The redundancy represents the percentage to which the correct (matched) extraction is redundant, i.e., it overlaps itself.
  The optimum value for the redundancy is 0.



(a) Matched extraction

(b) Matched reference

Figure 1: Matching principle

- $RMS = \sqrt{\frac{\sum_{i=1}^{l}(d(extr_i;ref)^2)}{l}}$

  l = *number of pieces of matched extraction*

  $d(extr_i;ref)$ = *shortest distance between the i-th piece of the matched extraction and the reference network*

  $RMS \in [0;$ *buffer width*$]$

  The RMS difference expresses the average distance between the matched extracted and the matched reference network, and thus the geometrical accuracy potential of the extracted road data. The value depends on the buffer width. If an equal distribution of the extracted road data within the buffer around the reference network is assumed, it can be shown that

  $$RMS = \frac{1}{\sqrt{3}} * \textit{buffer width}$$

  The optimum value for RMS is 0.

In the literature, there are several summarizing quality measures like quality, rank distance or branching factor. Under the assumption of no redundancy, these measures can directly be calculated from completeness (*compl*) and correctness (*corr*) as follows:

- *quality* $= \frac{\textit{length of matched extraction}}{\textit{length of extr.}+\textit{length of unmatched ref.}}$

  $= \frac{\textit{compl}\cdot\textit{corr}}{\textit{compl}-\textit{compl}\cdot\textit{corr}+\textit{corr}}$

- *rank distance* $= \sqrt{\frac{\textit{completeness}^2+\textit{correctness}^2}{2}}$

- *branching factor* $= \frac{\textit{length of unmatched extraction}}{\textit{length of matched extraction}}$

  $= \frac{\textit{compl}-2\cdot\textit{compl}\cdot\textit{corr}+\textit{corr}}{\textit{compl}\cdot\textit{corr}}$

Consequently, these three measures do not contain more information as completeness and correctness do. Therefore, in general, they are not very important, as completeness and correctness are much better interpretable. Only in cases where it is necessary to have just *one* measure describing the quality of the extraction result, one of the above measures might be selected. In such cases, the behavior of the measures subject to completeness and correctness should be analyzed to ensure that a measure is selected, which is suitable for the given task.

2.3 Evaluation of the network

The network properties are very important characteristics of the extraction result. Therefore, in addition to the intuitively feasible quality measures *completeness*, *correctness*, and *RMS*, an evaluation of the network properties of the extraction with respect to the reference is proposed. For this purpose, four quality measures are introduced: *Mean detour factor* and *mean shortcut factor* that evaluate to which degree the function of the network is fulfilled to provide efficient connections between distante places. *Topological completeness* and *topological correctness* serve as measures for the topology of the extraction with respect to the reference.

2.3.1 Function The measures *Mean detour factor* and *mean shortcut factor* evaluate, to what extent the extraction provides less efficient connections (detours) or more efficient connections (shortcuts) compared to the reference. Detours emerge from gaps within connected components of the extraction, shortcuts result from additional connections.

Given a minimum distance difference Δd, *mean detour factor* and *mean shortcut factor* are defined as follows: For each pair $(i, j), i \neq j$ of nodes[1] of the reference, which is connected in the reference and whose homologous nodes are connected in the extraction, the distance along the reference (*network distance*^{ref}) and the distance along the extraction (*network distance*^{extr}) are calculated based on a search for the shortest path between the respective nodes. A ratio r is defined for each such pair by

$$r = \frac{\textit{network distance}^{extr}}{\textit{network distance}^{ref}}$$

If

$$\textit{network distance}^{extr} - \textit{network distance}^{ref} > \Delta d$$

r is referred to as *detour factor*.

If

$$\textit{network distance}^{extr} - \textit{network distance}^{ref} < \Delta d$$

r is referred to as *shortcut factor*.

If

$$\left|\textit{network distance}^{extr} - \textit{network distance}^{ref}\right| \leq \Delta d$$

r is set to 1.0 and in the following, it is considered similarly as *detour factor* and as *shortcut factor*.

The *mean detour factor* is the mean of all *detour factors*. To avoid a bias of this mean, *detour factors* with $r = 1.0$, which are

[1] In this case, special care has to be taken about the insertion of auxiliary nodes for the matching. Details can be found in (Wiedemann, 2002a).

considered as *shortcut factors* as well, are introduced with half the weight of the *detour factors* with $r > 1.0$.

The optimum value for the *mean detour factor* is 1.

The *mean detour factor* increases with the number of important connections, which are missing in the extraction. In this context, "important" denotes that the lack of a connection leads to a significant detour between many pairs of nodes. What is more, the *mean detour factor* increases with the degree to which the extraction wiggles around the reference. This influence is reduced with increasing Δd.

The *mean shortcut factor* is the mean of all *shortcut factors*. To avoid a bias of this mean, *shotcut factors* with $r = 1.0$, which are considered as *detour factors* as well, are introduced with half the weight of the *shortcut factors* with $r < 1.0$.

The optimum value for the *mean shortcut factor* is 1.

The *mean shortcut factor* decreases with the number of additional important connections in the extraction. In this context, "important" denotes that these connections lead to significant shortcuts between many pairs of nodes. What is more, the *mean shortcut factor* decreases with the degree of generalization of the extraction with respect to the reference. This influence is reduced with increasing Δd.

The selection of Δd controls the effect of wiggling or generalized extraction on the two quality measures *mean detour factor* and *mean shortcut factor*.

2.3.2 Topology The quality measures *topological completeness* and *topological correctness* evaluate, to what extent the extraction provides too little or too much connections compared to the reference. Topological incompleteness results from too little connections, topological incorrectness from too much connections.

In order to calculate the *topological completeness*, firstly, all pairs of nodes are determined, which are connected in the reference. For these **CR** pairs, which are **c**onnected in the **r**eference, it is checked if their homologous nodes are connected in the extraction. This yields $\mathbf{CB^{ref}}$ pairs, which are **c**onnected in **b**oth networks. By means of that, the *topological completeness* is defined as

$$\textit{topological completeness} = \frac{CB^{ref}}{CR}$$

The optimum value for the *topological completeness* is 100%.

The *topological completeness* decreases with increasing fragmentation of the extraction with respect to the reference.

In order to calculate the *topological correctness*, firstly, all pairs of nodes are determined, which are connected in the extraction. For these **CE** pairs, which are **c**onnected in the **e**xtraction, it is checked if their homologous nodes are connected in the reference. This yields $\mathbf{CB^{extr}}$ pairs, which are **c**onnected in **b**oth networks[2]. By means of that, the *topological correctness* is defined as

$$\textit{topological correctness} = \frac{CB^{extr}}{CE}$$

The optimum value for the *topological correctness* is 100%.

The *topological correctness* decreases with an increasing number of wrong connections within the extraction.

[2] Note that $\mathbf{CB^{ref}} = \mathbf{CB^{extr}}$. This distinction is made only for the reason of a clear presentation.

2.4 Evaluation of crossings

Crossings are an essential part of the road network as they connect the roads to a network. The evaluation of the crossings is carried out similar to the evaluation of the roads. First, nodes of degree three or more are selected from the extraction and the reference. Then, these nodes are matched using a circular buffer.

The quality measures for the evaluation of crossings are:

- $\textit{completeness}_{\textit{crossings}}$
- $\textit{correctness}_{\textit{crossings}}$
- $\textit{redundancy}_{\textit{crossings}}$
- $\textit{RMS}_{\textit{crossings}}$

These measures are defined analogously to the respective measures for roads, whereas at each case, the definition is used, which refers to the number of matched/unmatched nodes (cf. Sec. 2.2). In addition to these measures, further measures could be thought of, e.g., based on the degree of the nodes and on the directions of the branching roads.

3 PRACTICAL APPLICATION

3.1 Simulated data

In Tab. 1, a simulated reference as well as five different simulated extraction results are presented together with their respective evaluation results. *Extraction 0* is identical to the reference data. Consequently, all quality measures take their optimum values. In *extraction 1*, one road is missing. This leads to a sligh decrease of the *completeness* and to an increase of the *mean detour factor*. An additional road has been added in *extraction 2*, which leads to a reduced *correctness* and a *shortcut factor* smaller than one. In *extraction 3*, the central parts are disconnected to the rest of the extraction, which — besides a minor decrease of the *completeness* — leads to a significant decrease of the *topological completeness* as well as to a *mean detour factor* larger than one. Finally, in *extraction 4*, a road has been added, which connects the two components that are not connected in the reference. This kind of change is indicated by the lower values of the *correctness* as well as of the *topological correctness*. Besides, also the quality measures for the crossings correctly indicate all the changes applied to the simulated extraction results.

3.2 Real data

In this section, the evaluation of the extraction results of two different approaches for road network extraction are presented. The first approach uses local grouping for the generation of a road network from lines, which were extracted using a sophisticated line extraction approach (Steger, 1998). The grouping step is similar to the one presented in (Vasudevan et al., 1988). The second approach uses the network properties of roads for their extraction and tries to reconstruct the crossings explicitly (Wiedemann, 1999, Wiedemann, 2002b). Both approaches were applied to the image presented in Fig. 2, which has a ground pixel size of 2 m. The evaluated results of the two approaches are shown in Figs. 4 and 5, the respective reference data in Fig. 3. In this case, the reference data was captured manually from high resolution aerial imagery. The evaluation (see Tab. 2) shows that the extraction results are almost similar with respect to completeness and correctness. Concerning the network properties, it is obvious that the results based on local grouping have some deficiencies. This is also true for the crossings, where all measures signalize that the explicit reconstruction of crossings pays off.

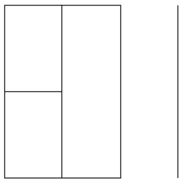
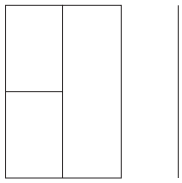
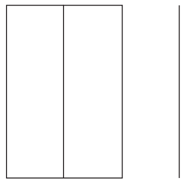
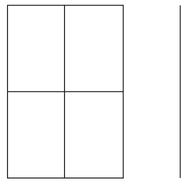
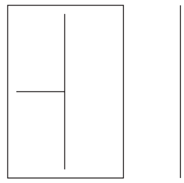
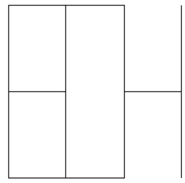
Reference	Extraction 0	Extraction 1	Extraction 2	Extraction 3	Extraction 4
					
Roads					
Completeness	100.0 %	94.1 %	100.0 %	97.4 %	100.0 %
Correctness	100.0 %	100.0 %	94.4 %	100.0 %	94.4 %
Redundancy	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
RMS	0.0 m	0.0 m	0.0 m	0.0 m	0.0 m
Network					
Top. Completeness	100.0 %	100.0 %	100.0 %	62.8 %	100.0 %
Top. Correctness	100.0 %	100.0 %	100.0 %	100.0 %	70.7 %
Mean detour factor	1.00	1.75	1.00	1.11	1.00
Mean shortcut factor	1.00	1.00	0.77	1.00	1.00
Crossings					
Completeness	100.0 %	50.0 %	100.0 %	25.0 %	100.0 %
Correctness	100.0 %	100.0 %	80.0 %	100.0 %	66.7 %
Redundancy	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
RMS	0.0 m	0.0 m	0.0 m	0.0 m	0.0 m

Table 1: Simulated data and the respective evaluation results

Figure 2: Image data

	local grouping	using network properties
Roads		
Completeness	85.8 %	89.3 %
Correctness	98.5 %	98.0 %
Redundancy	-0.4 %	-1.0 %
RMS	1.55 m	1.54 m
Network		
Top. Completeness	34.2 %	97.1 %
Top. Correctness	100.0 %	100.0 %
Mean detour factor	1.40	1.03
Mean shortcut factor	0.99	0.99
Crossings		
Completeness	58.3 %	63.9 %
Correctness	56.2 %	82.1 %
Redundancy	41.6 %	0.0 %
RMS	4.4 m	3.9 m

Table 2: Evaluation results

4 SUMMARY AND OUTLOOK

Automatic evaluation of the obtained results is an increasingly important topic in image analysis as results are approaching a point where they become useful for practice. In this paper a methodology for the evaluation of automatic road extraction algorithms based on the comparison to manually plotted reference data is presented. This methodology was tested using simulated as well as real road extraction results. The proposed evaluation scheme adequately captures the characteristics of the individual extraction results and can thus serve as a basis for their comparison.

Depending on the application at hand some of the quality measures may be more relevant than others. Additional measures could be thought of, e.g. for a more sophisticated evaluation of the crossings.

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Figure 3: Reference data

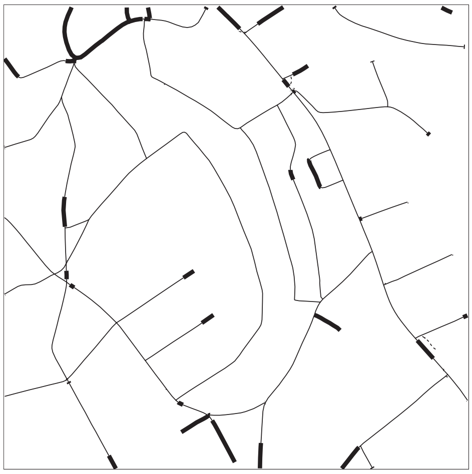

Figure 4: Extraction using local grouping (thin lines: correct extraction; thick lines: missing extraction; dashed lines: incorrect extraction)

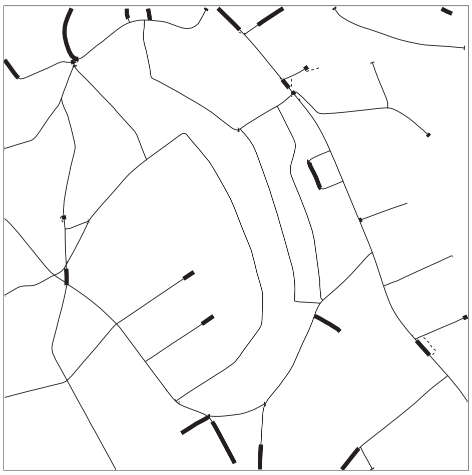

Figure 5: Extraction using network properties (thin lines: correct extraction; thick lines: missing extraction; dashed lines: incorrect extraction)