AUTOMATIC EXTRACTION AND EVALUATION OF ROAD NETWORKS FROM MOMS-2P IMAGERY

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ABSTRACT

In this paper an approach for the automatic extraction and evaluation of road networks from MOMS-2P imagery is proposed. Due to the limited spatial resolution of the images for the specified task a road model purely based on local criteria is rather weak, and therefore a significant number of false alarms are to be expected. A model is defined based on the local, regional, and global properties of the road network and a corresponding extraction strategy is derived. The extraction strategy incorporates line extraction using a differential geometric approach, followed by constructing a weighted, planar graph from the lines and the gaps between them according to local (radiometric) and regional (geometric) criteria. By computing various "best paths" through this graph the actual network is derived based on global (topological) criteria. Line extraction is carried out for all available channels, and the individual results are fused prior to grouping. Thus, the information from multiple spectral channels is exploited. The evaluation of the results is carried out by comparison to manually derived reference networks showing the feasibility but also the problems of the approach.

1 INTRODUCTION

For the development of a large number of countries topographic mapping from space must be regarded as a necessity (Konecny and Schiewe, 1996). Today, many suitable and operational sensors exhibiting various spatial, spectral, and temporal resolutions and continuously delivering raw imagery are in orbit, and more are to come. Thus, the time- and cost intensive manual procedure necessary for turning these images into useful geographic information constitutes the main bottleneck, which needs to be overcome. The solution is an increase in automation in order to improve the efficiency of satellite topographic mapping. However, existing methods, which are mainly based on multi-spectral classification, in general lack the necessary flexibility, robustness, and reliability mandatory for practical use.

MOMS-2P (Modular Optoelectronic Multispectral Scanner) was developed for mapping of the Earth's surface from space (Seige, 1997, Steinborn, 1995). The three-line pushbroom camera is mounted on the Russian PRIRODA module attached to the space station MIR. It delivers imagery with a ground resolution of 6 m in the high resolution panchromatic nadir channel and 18 m in the two panchromatic stereo channels as well as in the four multi-spectral nadir channels.

In this paper an approach is proposed for the automatic extraction and evaluation of road networks from MOMS-2P imagery. It extends the approach of (Steger et al., 1997) by fusing multiple images of different radiometric and/or geometric resolutions and by the additional use of local (radiometric) and regional (geometric) characteristics of roads. Preliminary results of this work have been reported in (Heipke and Wiedemann, 1997). In the following section, a number of references about road extraction from images are discussed. Then, the used model and extraction strategy for road networks are presented. Section 4 deals with the evaluation of automatic road extraction and in section 5 results from the current implementation of the proposed approach are presented and evaluated. The paper concludes with a summary and an outlook.

2 PRIOR WORK ON ROAD EXTRACTION FROM IMAGERY

Many approaches for the automatic extraction of roads from satellite imagery can be found in the literature. Additionally, approaches for high resolution imagery which make use of the network characteristic of roads are of interest for this paper. One problem for the extraction of roads from satellite imagery is the low spatial resolution of the image data. This implies that many details of roads are not visible in the images and therefore cannot be used for extraction. (Cleynenbreugel et al., 1990) motivate the use of additional knowledge sources like context (e.g., land cover regions from a geographical information system), height information from a digital terrain model, and old road-maps. According to the actual context as derived from these additional knowledge sources different road models are employed. Two different approaches for the extraction of roads from SPOT imagery are presented, each being optimized for a particular context area: The first is designed for the extraction of forest roads and favors the extraction of rectangular structures. The second is optimized for mountain roads and considers height and slope constraints. Update of topographic maps from satellite imagery (SPOT) is presented in (Solberg, 1992). In the first step a verification of the existing road map is performed by comparison of extracted lines with the old road data. New roads are detected by line extraction and local grouping in a second step. Isolated lines, i.e., lines which cannot be connected with other lines are removed. The update of the old road map is carried out based on visual comparison of the detected roads with the old road map and the image data. In (Busch, 1996) low level line extraction is performed using SPOT imagery. A line following approach which considers direction and gray value constraints is used to determine if neighboring lines can be connected with each other. It is initialized at the end point of one line (starting line). If another line with statistically the same spectral characteristics as the starting line is reached within a given distance, these two lines are connected. For distinction between roads and other linear features multi-spectral classification is proposed.

In contrast to the approaches cited above which use local grouping the following approaches at least implicitly make use of the more global network characteristic of roads, which can provide important additional information. In (Fischler et al., 1981) a road connecting two given points of the road network is searched for. Different low level operators for road extraction from low resolution aerial images are classified into two types: Type I operators are assumed to deliver no false extractions, but some roads might not be found. Type II operators may yield false extractions but are assumed to extract all roads completely. In regions where a type I operator has detected a road, the scores of every type II operator is set to a maximum value (zero costs). In this way multiple type II operators are made commensurate. The result of each type II operator is stored in a cost array. Between two given points the best path is calculated for each type II operator using the F^* algorithm. The path which yields the lowest so-called "self normalized average cost" per pixel is chosen as the road. In (Merlet and Zerubia, 1996) the F^* algorithm is extended to cliques and to neighborhoods larger than one. By means of the cliques it is possible to introduce contrast information into the calculation of the minimum cost path and the larger neighborhoods allow for the consideration of the curvature of the final path. Presented results are based on SPOT imagery. Snakes are used for the extraction of linear features from SPOT imagery in (Li, 1997). The resulting equations are formulated in a least squares approach which in contrast to the conventional snake approach (Kass et al., 1987) allows for an evaluation of the quality of the estimated parameters. The approach can handle multiple images. This is shown to be advantageous in case of occlusions which occur only in a subset of the used images. The initialization of the snakes is carried out manually, i.e., the interpretation task is taken over by an operator. An approach which mainly deals with the network character of roads is described in (Vasudevan et al., 1988). After line extraction from Landsat TM imagery neighboring and collinear lines are searched for. For each line the best neighbor is determined based on the difference in direction and the minimum distance between the end points. Connected lines form so-called line clusters which represent parts of the road network.

(Ruskoné et al., 1994) present an approach for road network extraction on high resolution imagery. In the first stage a low level road tracker following homogeneous elongated areas is started at automatically extracted seed points. In the second stage hypotheses for the connection of the extracted road parts are generated and checked based on geometric criteria like distance and direction. The final stage consists of a geometric adjustment of the extracted road network based on snakes. A road network is generated in (Mayer et al., 1997) based on the extraction of roads and crossings. The approach exploits the scale-space behavior of roads. Lines in coarse scale are used for the initialization of ribbon snakes in fine scale. Results of the snake optimization process are accepted or rejected as so-called salient roads based on their width variations. Gaps between salient roads are bridged using zip-lock snakes (Neuenschwander et al., 1995). Hypotheses for junctions are generated from line extraction in coarse scale. A closed snake is positioned at each junction hypothesis. Its outline is expanded and optimized. A junction is verified if it can be connected to at least one of the adjacent roads. In (Steger et al., 1997) the necessity of global grouping instead of a purely local determination of the continuation of the road is underlined. Each possible connection between road candidates is regarded as a gap. A weight is assigned to each gap which depends on the lengths and directions of the gap and of the adjacent road candidates. Thus a weighted graph is constructed. Seed points for the road network extraction are selected on road candidates close to the border of the image. For each pair of seed points the best path is searched through the weighted graph.

3 MODEL AND EXTRACTION STRATEGY FOR ROAD NETWORKS

Due to the limited ground resolution of traditional satellite images a **road model** purely based on local characteristics is rather weak. Therefore, a significant number of false alarms are to be expected. For this reason, the **road network** is also considered, and regional, and global properties are incorporated into the object space model:

Locally, radiometric properties play the major role. The road is modeled as a line. It can have a higher or lower reflectance than the surroundings.
Geometry is explicitly introduced on the **regional** level. Regional characteristics incorporate the assumption that roads are composed of long, straight, and horizontal segments.
Globally, roads are described in terms of topology: the road segments form a network, in which all segments are topologically linked to each other.

It should be noted that the appearance of roads in the various channels of the multi-spectral images may deviate from the object space model, e.g., due to different contrast of the images, occlusions, shadows, or aliasing effects. Also, roads in different parts of the world exhibit different characteristics. The notion of straightness, for example, is more pronounced in a road in Australia than in Central Europe.

The **extraction strategy** is derived from the model and is composed of different steps. After line extraction and preprocessing, a weighted graph is constructed from the lines and the gaps between them. Road network generation is carried out by calculation of "best paths" between various pairs of points which are assumed to lie on the road network with high probability. The approach uses local (radiometric) as well as regional (geometric) information for line extraction and weighting and global (topological) information for the network generation. In the following a detailed description of each step is given.

Line extraction is performed in multiple images of different radiometric and/or geometric resolutions separately. It captures the local radiometric road characteristics. Line extraction is carried out using an approach based on differential geometry (Steger, 1998). The approach is initialized by a few, semantically meaningful parameters: The maximum width of the lines to be extracted as well as two threshold values which control the process of linking individual line pixels into pixel chains. The maximum width can be chosen according to the road width scaled to the image. The threshold values can be derived from the gray value contrast between roads and their surroundings. In addition it can be decided whether bright or dark lines shall be extracted. The result of the line extraction is a set of pixel chains and junction points for each image at sub-pixel precision. Due to the exclusive use of local road characteristics the result is not complete and contains false alarms, i.e., some roads are not extracted and some extracted lines are not roads.

Line preprocessing has three different tasks:

1. Increase the probability that lines either completely correspond to roads or to linear structures not being roads.
2. Fuse lines extracted from different images.
3. Prepare lines for the generation of junctions.

Lines are not split during the final extraction step (road network generation), i.e., either they are completely added to the road network or they are not added at all. Therefore, it is necessary to ensure that lines either completely correspond to roads or to linear structures not being roads, and lines have to be split at the point where they cross the roadside. The analysis of several attributes which can be calculated for lines like, e.g., curvature, width, and gray values, has shown that the most significant feature for a change in the line semantics ("road"/"not road") is high curvature. Therefore, lines are split at points where the curvature exceeds a given threshold.

To make use of the multi-spectral information, the lines extracted from different images are fused by a union operation. In addition, redundantly extracted lines are eliminated, i.e., if a line (or a part of it) which was extracted in a slave image lies within a given distance around a line extracted in another image (master image), it is assumed to be redundant and therefore it is eliminated. A natural choice for the master image is, e.g., the image with the higher spatial resolution. The eliminated lines are stored for weighting the remaining lines.

Junctions are an essential part of the road network, but they might not be detected completely during line extraction. To prepare the generation of missing junctions, lines are split at points which are candidates for being a junction. These are points close to other line ends, as, e.g., point **P** in Figure 1 which lies on line $\mathbf{l}_1$ close to the end of line $\mathbf{l}_2$.

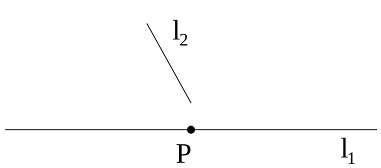

Figure 1: Candidate for a junction

In order to introduce regional characteristics into the extraction strategy, a **weighted graph** is constructed from the lines. The nodes of the graph are the endpoints of the lines, the edges are the lines and gaps (see below). Linear fuzzy functions (Zadeh, 1989) are used to transform the following properties of the lines into partial weights:

- Length (before the splitting of the lines which leads to new junctions)
- Straightness
- Gray value homogeneity
- Degree of overlap with lines extracted (redundantly) from other images

An intermediate weight for each line is derived by combination of the respective partial weights using the fuzzy "and" operator. The final weight is calculated for each line by dividing the length of the line by its intermediate weight. The final weights thus correspond to costs, which are assigned to the respective edges of the graph.

In general, the lines are not connected to each other, especially, if they originate from different images. Each pair of endpoints of different lines defines a gap. If the length of a gap does not exceed a given threshold, partial weights are derived from

- The absolute gap length
- The relative gap length (compared to the adjacent lines)
- The collinearity of the adjacent lines and the gap
- An additional constraint which ensures that the weight of a gap cannot become higher than that of the adjacent lines

Intermediate weights for the gaps are calculated as in the case of lines. For each gap which has an intermediate weight grater than zero, an edge is inserted into the graph which receives as final weight (cost) the length of the gap divided by its intermediate weight. Thus, bridging of gaps is made possible. Because gaps which are too long or which received a weight equal to zero are not inserted into the graph, the graph may contain several connected components. Note that the decision which gaps are to be bridged is not taken purely based on the regional criteria used for weighting the gaps, but also considers the global network characteristics of roads.

The **road network generation** is carried out in a hierarchical way using the global network characteristics: In the first step, major roads leading from one image border to another are searched for. Therefore, the endpoints of lines near the image border which have a relatively high weight (low cost), i.e., which are assumed to be part of the road network, are selected as seed points. Between each pair of seed points, the path is calculated through the weighted graph which minimizes the costs ("best path") using the Dijkstra algorithm (Sedgewick, 1992). If such a path exists, i.e., if the seed points lie within the same connected component, it is added to the road network. In the second step, minor roads which yield additional connections between major roads are to be extracted. As roads are connected with other roads by junctions, candidates for junctions are searched for along the current road network. The best path is calculated between each pair of candidates for junctions and added to the road network. This step is iterated until no new candidate for a junction is found. In the current implementation, the second step as described above is not yet contained. Instead of this, the best path is calculated for each pair containing one seed point (cf. first step) and one end point of a line which has a high weight and which does not lie near the border of the image.

It should be noted that the resulting network is inhomogeneous with respect to the geometric accuracy: its parts originate from line extraction in images of different ground resolution as well as from a purely geometry-based gap bridging.

4 EVALUATION

Internal self-diagnosis and external evaluation of the obtained results are essential for any automatic system. In the long run these factors are of major importance for the introduction of the system into practical applications. Both, internal self-diagnosis and external evaluation should yield quantitative results which are independent of a human observer. Internal self-diagnosis can be based upon 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 reference data of some sort and compares them to the automatically obtained results. Here, it is dealt with the external evaluation of the automatically extracted road data by means of comparing them to manually plotted linear road axes used as reference data. In the following the evaluation procedure is briefly described. More details can be found in (Heipke et al., 1997).

The comparison is carried out by matching the extracted data to the reference data using the so-called "buffer method", in which every portion of one network within a given distance (buffer width) from the other is considered as matched. For the evaluation of the road extraction results a number of quality measures is defined based on the matching results. Two questions are thought to be answered by means of the quality measures: (1) How complete is the extracted road network, and (2) How correct is the extracted network. The completeness tells how much is missing in the network, whereas the correctness is related to the probability of an extracted linear piece to be indeed a road.

For the actual evaluation first, four values are computed: the length of the reference data, the length of the extracted data, the length of the matched reference data, and the length of the matched extracted data. Completeness is then defined as the percentage of the reference data which is explained by the extracted data, i.e., the percentage of the reference data which lies within the buffer around the extracted data:

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

The correctness represents the percentage of correctly extracted road data, i.e., the percentage of the extracted data which lie within the buffer around the reference network:

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

In addition, also the geometric accuracy of the extraction is assessed. It is expressed as the RMS difference between the matched extracted and the matched reference data.

5 RESULTS

The proposed approach was tested using MOMS-2P imagery taken over Victoria, Australia approximately 150 km west of Melbourne (data take 0814 from December 11, 1996 at 12:30 local time). The area mostly consists of open rural country, is somewhat hilly, and contains wide and straight roads. The images were acquired in mode C, i.e., besides the high resolution panchromatic channel with a ground resolution of approximately 6 m three spectral channels (green, red, infrared) with a ground resolution of approximately 18 m are available. Instead of computing orthoimages, an image-to-image registration was performed using two perpendicular shifts only. This simple registration was found sufficient due to the small difference in viewing angle between the high resolution and the multi-spectral scene.

Two parts of the imagery described above were processed, each covering an area of about 6 by 6 km^2 on the ground. They are displayed in Figure 2. For road extraction on both parts, the high resolution panchromatic image was used together with the infrared image and the Normalized Difference Vegetation Index (NDVI) (Gallo and Eidenshink, 1988):

$$NDVI = \frac{IR - R}{IR + R}$$

where: IR . . . reflectance value in infrared domain
R . . . reflectance value in red domain

By visual inspection of the images it was found that roads appear brighter than their surroundings in the panchromatic image and darker in the infrared and the NDVI image. The line extraction algorithm was initialized accordingly.

The approach proposed in chapter 3 was applied to the described images of the first part of the test scene. Figure 3 shows on the left the resulting road network and on the right the manually plotted reference data. Numerical values for the quality measures were computed as described in chapter 4. The buffer width was set to 12 m. A completeness of 70% and a correctness of 81% are achieved on this part. The geometric accuracy as described by RMS differences is below 5 m. Some parts of the road network were not extracted due to low contrast over long sections. Some parts of the extraction do not correspond to roads. In this example, false extractions are highly curved. This occurs because straightness is not accounted for during the road network generation. In other words, the direction difference of each two adjacent edges is not taken into account by the search for the best paths.

The results for the second part of the test scene are displayed in Figure 4 (left). The according reference data is shown in Figure 4 (right). The resulting completeness is 45%. The correctness amounts to 81%. The geometric accuracy is about 4 m. This example shows the limitations of the approach. Parts of the road network were not found by line extraction because the road model did not fit the actual roads in the images. In some parts the contrast between the roads and the surroundings was too low, in other parts the road apparently was occluded by vegetation. Some of the resulting gaps are too long to be bridged. If two such gaps occur along one road, the part between these gaps will not be extracted because there is no connection between this part and the remainder of the road network. I.e., two long gaps along one road may prevent the extraction of this road.

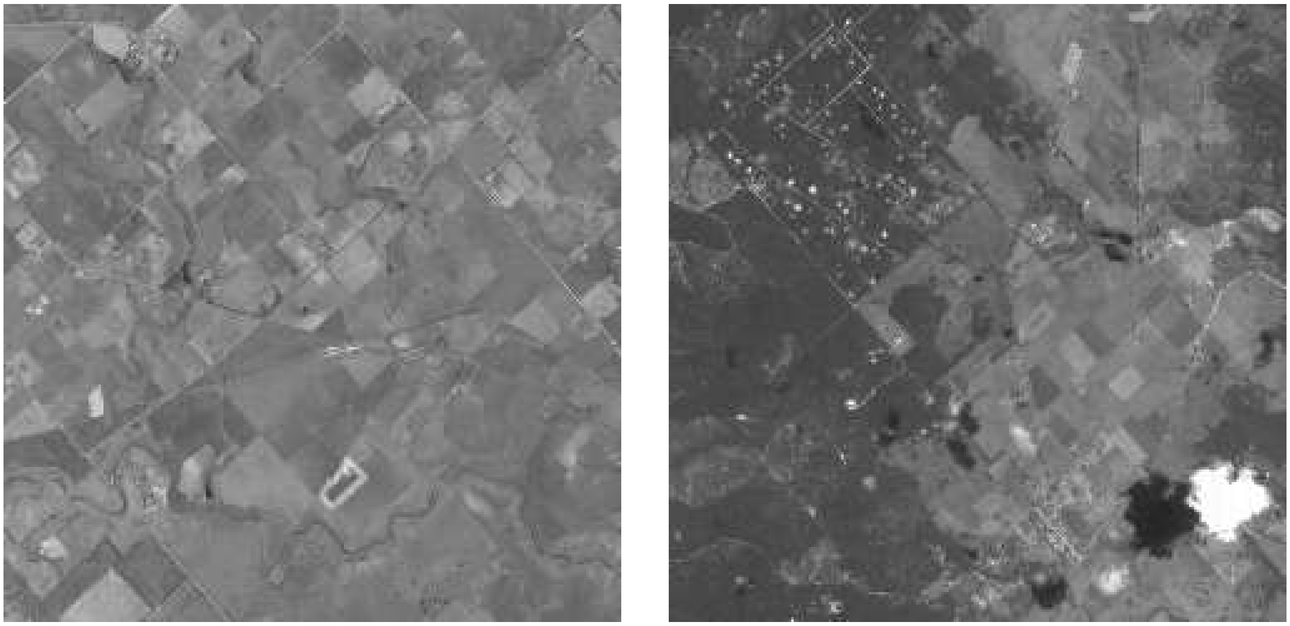

Figure 2: First (left) and second (right) part of the test scene, high resolution channel

6 SUMMARY AND OUTLOOK

This paper deals with the extraction of road networks from high resolution multi-spectral satellite imagery. A model for the road network and an extraction strategy derived from the model were presented. Furthermore, a method for automatically evaluating the quality of the extraction results based on independent reference data was briefly described. Results using MOMS-2P images taken over Australia were reported and discussed.

Future work will be directed towards improvements of the model and the extraction strategy according to the problems mentioned in Section 5. The number of false extractions may be reduced by adding only straight paths to the road network. The problem that two long gaps may prevent the extraction of a whole road may be solved by an improved seed point selection where also connections between two seed points both lying apart from the image borders are searched for. Furthermore, the geometric accuracy of the whole road network might be homogenized by the use of snakes which are initialized from the extracted road network. Main improvements are expected at parts of the road network which result from line extraction from low resolution images. Research will also be directed to the analysis of the support which can be provided to automatic road extraction by the use of existing data from geographical informations systems.

With the advent of the 3 m and 1 m satellite images announced for already some time now, image analysis approaches like the one described in this paper will become more popular within remote sensing. These images have the potential to overcome the limitations of multi-spectral classification, since modeling can be based on geometric, radiometric, and semantic characteristics of the object scene rather than only on statistics of pixel brightnesses.

The automatic evaluation of the extraction results will receive an increasing amount of attention, since the quality of the results is a decisive factor in the introduction of the image analysis into practical work. Thus, the challenges for research and development in this area are laid out. Time will show whether they can be successfully met.

7 ACKNOWLEDGMENTS

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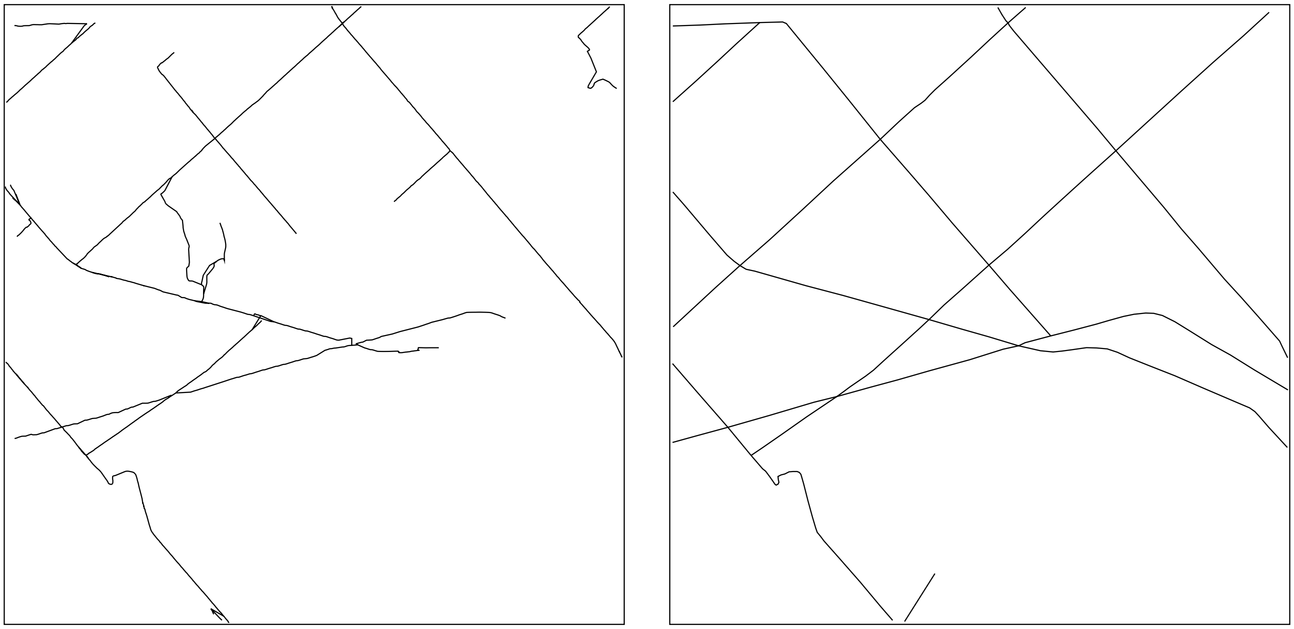

Figure 3: Extraction result (left) and reference data (right) for the first part of the test image

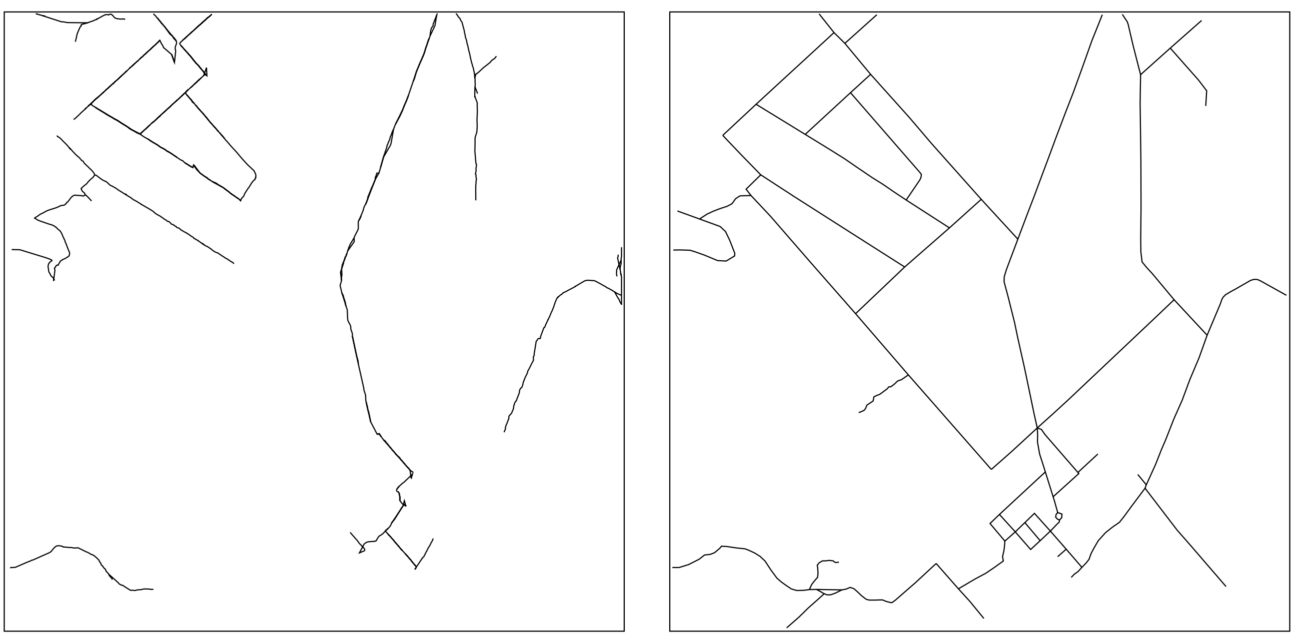

Figure 4: Extraction result (left) and reference data (right) for the second part of the test image