ROAD NETWORK EXTRACTION FROM SAR IMAGERY SUPPORTED BY CONTEXT INFORMATION

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ABSTRACT

This paper deals with automatic road extraction from SAR imagery. In general, automatically extracted road networks are not complete, i.e., gaps remain in the erxtracted network. Especially in SAR imagery many objects occlude road sections and cause gaps, due to the side looking geometry of the SAR sensor. In this paper an approach for automatic road extraction is proposed that is optimized for rural areas by using additional explicitly modeled knowledge about roads and the context of roads. Roads are modeled as a network. Context of roads is hierarchically structured into a global and a local level. Local context objects like trees or vehicles can interfere road extraction due to the layover effect or the motion, but they can also support it. It is shown that the incorporation of local context objects into the extraction improves the results by bridging smaller gaps. Though the approach is restricted to rural areas, other global context regions can provide additional information, too. Here, urban areas are used to deliver confident seed information for the road network generation, because it is the characteristic and function of roads to connect urban areas with each other. With this information a more complete network is extracted. Furthermore, a new approach for highway extraction is proposed based on a multi-scale modeling. Because of the larger dimensions of highways and the more salient substructures, like the crash barriers, a more detailed model and extraction strategy is needed. Finally, examples and results are given, showing the potential of using context information and explicit modeling of roads for automatic road extraction from SAR imagery.

1 INTRODUCTION

Up-to-date road network data are required by many applications, e.g. topographic mapping, traffic monitoring, or navigation. Extensive research has been done to automate the extraction and update of road networks. For automatic road extraction from images with low resolution the most common techniques rely on the detection and following of lines. Because SAR is (almost) independent from weather and daylight conditions, the extraction of road networks from SAR imagery received notable attention over the past years. Beside the advantages of SAR, road extraction from this type of imagery has also to cope with a lot of difficulties, especially with well-known SAR inherent effects like layover and shadow caused by adjacent objects.

In this paper, an approach for automatic road extraction from SAR imagery is presented, that is based on the extraction of lines and explicitly modeled knowledge of roads. The approach is extended by the use of context information and, moreover, by a more detailed model for highways. Context information means knowledge about the road and its spatially neighbored objects. The relations are modeled on a local and on a global level. Local context objects influence the appearance of a road section, e.g., vegetation or buildings with its corresponding layover and shadow. The global context region residential areas are always connected by roads. Therefore, the contours of residential areas allow to provide confident seed information for the road extraction.

In this paper the road extraction approach is successively extended by three add-ons. In the first extension, different local context objects are exemplarily introduced into the extraction. Then, in the second extension, global context regions are introduced. In the last extension, the approach is extended by a more detailed model for the road class "highway". Because of the larger dimensions of highways and the more salient sub-structures (e.g. crash barriers) special focus is on multi-scale modeling and incorporating reflection characteristics. The paper starts with a model for each extension (Sect. 2). Then, extraction methods are outlined (Sect. 3) and finally, the results are evaluated for each extension (Sect. 4).

2 MODEL FOR ROADS AND CONTEXT INFORMATION

The appearance of roads in digital imagery strongly depends on the sensors spectral sensitivity and its resolution in space. The proposed model is restricted to SAR imagery with a resolution of about 2 m per pixel. The used imagery are multilook X-band data with a ground resolution of about 2 m (E-SAR, DoSAR) and up to 1 m resampled AeS-1 data, originally 0.5 m. The model below describes in the first part the characteristic properties of roads (Sect. 2.1). The second part defines different context information levels (Sect. 2.2) and in the third part a complex model for the object "highway" in SAR imagery is given (Sect. 2.3).

2.1 Roads in open rural areas

In a resolution of about 2 m roads appear mainly as lines with the following characteristics:

- Radiometric characteristics: low and homogeneous reflection (because the smooth surface leads to total reflection)
- Geometric characteristics: low curvature, constant width, elongated segments (because of road construction constraints)
- Topological characteristics: roads form a network









(d) Bridge and traffic signs

(a) Layover effects of trees on road section

(b) Blurred vehicle moving in azimuth direction

Figure 1: Local context objects

In open rural areas the appearance of roads corresponds reasonably well to this model. Lines representing road centerlines can be extracted in a stable manner. Whenever the complexity of the scene increases, interactions between roads and other objects appear frequently, e.g., neighbored objects cause shadow/layover regions, or moving vehicles cause bright peaks blurred in azimuth direction. In such situations, the line model holds no longer and an extraction system relying purely on such a model would be rather weak. It is necessary to take context information into account.

2.2 Context information

The model for roads is now extended by context information. Context, in general, is restricted to knowledge about relations of the object of interest to other neighboring objects (Stat and Fischler, 1995). For roads, two levels of context can be distinguished like in (Baumgartner et al., 1999).

- Local context describes knowledge about relations between roads and spatially neighbored objects (context objects).
- Global context is characterized by the presence of other objects in the larger region (context regions). In (Baumgartner et al., 1999) it is used to define an appropriate extraction technique .

Here, both context levels will be taken into account. For determining the relevent context objects and regions for roads in SAR imagery, a detailed analysis was carried out. Therefore, the road extraction of Sect. 3.1 was applied to indicate the difficulties. The false alarms and gaps in the road network were examinated carefully.

2.2.1 Local context objects Situations in which neighbored objects make road extraction locally difficult are caused by the following local context objects. They are illustrated in Figure 1.

- layover and shadow regions caused by buildings and alleys
- blurred bright stripes caused by vehicles moving in azimuth direction
- road junctions
- bridges (indicated by the high backscattering of the metal barriers at the sides of the bridge and corner reflector interaction with the ground)
- large traffic signs at highways

Many of the context objects are characterized by a high backscattering caused by metallic structures or by multiple bounces: individual trees, larger traffic signs, bridges, blurred vehicles, etc. These phenomena exist in all SAR data, in E-SAR data as well as in AeS-1 data. In order to make it possible to use these objects as positive evidence for roads during the road extraction, they have to be explicitly modeled. **2.2.2 Context regions** The road extraction depend also on the region where it is applied, i.e., on the global context. For instance, roads in urban areas have a quite different appearance from roads in forest areas or in rural areas. Precisely because the influence and presence of neighbored local objects and the density of those objects. For roads three global context regions are distinguished here, *rural, urban,* and *forest areas*. In rural areas the mentioned context objects are casual distributed, in contrast to forest and urban areas where trees and buildings are more frequent. Experience shows that approaches that are suitable for road extraction in rural areas usually cannot be applied in other global contexts without modification. Often a completely different approach is required. Therefore, forest and urban areas are initially mask out for the extraction of rural roads (Figure 2).

But urban areas are a high indicator for roads: Roads are organized as a network connecting all areas inhabited and exploited by human beings. This semantical function of roads can be used, because it comprehends a reliable seed information for the road extraction.



Figure 2: Global context

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2.3 Highways

In contrast to rural roads, highways are mostly wider and for the side looking radar less occluded by context objects. A separate, detailed model for highway is set up in the following. Highways comprise two (anti-)parallel roads that are bordered by crash barriers. To extract such types of objects, the use of a multi-scale model has proven to be very important (see e.g. (Hinz and Baumgartner, 2003)). In the highest resolution, a highway is characterized by two parallel dark lines separated by a thin bright line, the central crash barrier. This crash barrier is a reliable feature, because metal objects produce a strong radar backscattering. Figure 3(a) illustrates this and some more typical effects depending on the viewing angle: (A) Crash barriers orientated approximately in azimuth direction appear very bright, because of the corner reflector effect. (B) In other orientations, the high reflection of the crash barrier is still present. (C) There are also some areas without any reflection. These are caused by radar shadows in case of very high objects nearby. (D) The corresponding

(c) Junction



Figure 3: Appearance of highways in SAR images (a) Orientation dependent effects (b) Highways in reduced resolution, about 6 m

complement are layover areas smearing over the road. (E) Additionally, context objects like bridges (also traffic signs, tunnels, and vehicles) can be present.

In the same image but with reduced resolution, the fundamental structure of a highway is emphasized (Figure 3(b)). It appears as a dark, smooth-curved line, and the crash barriers are no more visible. However, a total corner reflection ("A" in Figure 3(a)) may avoid the annihilation of the crash barrier at lower resolutions. Hence, we restrict this part of the model to highway orientations that deviate from the azimuth direction significantly.

3 ROAD EXTRACTION

3.1 Road extraction in rural areas

The approach used for automatic road extraction in rural areas has been originally designed for optical imagery with a ground pixel size of about 2 m (see (Wiedemann and Hinz, 1999), (Wiedemann and Ebner, 2000)) and was adapted to SAR data (Wessel et al., 2002).

The first step of the road extraction consists of line extraction using Steger's differential geometry approach (Steger, 1998). It can be performed in multiple images and with different parameters settings for the individual road classes (highways, main roads, secondary roads). In the next step, the lines of each extraction are evaluated according to their road characteristics: curvature, width, reflectance properties etc. Then, with the confidence measures thus gained, overlapping lines are fused using a "best first" strategy and a weighted graph of road segments is constructed from the resulting (unique) set of lines. For allowing the elimination of gaps in the line extraction, candidates for supplementary road segments are added to the graph - typically resulting in an over segmented intermediate extraction. To extract the road network from the graph, seed points are defined (i.e. high rated road segments) and connected by optimal paths through the graph. The union of these paths corresponds to the final road network.

3.1.1 Extraction with context objects The road extraction algorithm allows to introduce additional segments together with confidence measures (weights) on the basis of the above mentioned fusion. This property is used to introduce context objects. At the time being, we assume that it would b possible to extract these objects quite reliably. In the current state of the implementation, the extraction of local context objects is done manually because, at the moment, the main task is to find out whether context information is useful for road extraction or not. Advanced studies for an automatic extraction of some of the context objects can be found in the literature (Kirscht, 1998), (Kirscht and Rinke, 1998), (Barsi et al., 2002). For introducing context objects into the extraction process it is important to (1) estimate the evidence each context object provides for roads and (2) choose an appropriate representation form for each context object: High evidence for roads is provided by context objects that almost exclusively

appear in conjunction with roads and rarely elsewhere. Therefore, vehicles blurred in azimuth direction, and also bridges, get high weights. Their representation form is a line. Other objects provide less evidence for roads. For example, alleys appear nearby roads but also elsewhere. They are henceforth represented as lines attached with low weights. Large traffic signs only appear together with roads. However, their correct (automatic) interpretation is assumed to be quite hard, so that they are added to the graph as middle-weighted short straight lines. The same is true for junctions, i.e. intersection points of roads. They are modeled as low weighted points in the graph with several terminals that allow connections between three or more lines.

3.1.2 Extraction with context regions Until now, context regions are simply used to exclude urban and forest areas from the extraction (Sect. 3.1). This was done because the computation time increases with the number of potential road segments, which is extremely high in the above mentioned regions. For this task a *urban-forest-mask* was generated, which can be extracted directly from the SAR data. A classification of X- and full-polarimetric L-band data allows to extract rural, urban and forest areas, based on the intensity values, ratios, and neighborhoods.

Furthermore, urban areas are now used as seed information in the road extraction procedure. We introduce the contours of urban areas as additional weighted segments in the same way as described in Sect. 3.1.1. The evidence for urban areas to be a seed point is very high. The advantage of introducing the contour line is threefold. First, no further hypotheses or extraction attempts of roads inside the city outline have to be made. Second, the function of cities to link road parts together to a network without interruptions by urban areas is fulfilled. Third, the contours are especially helpful in the vicinity of urban areas because often, the roads are not clearly visible in those regions.

3.1.3 Extraction of highways The extraction strategy for highways consists of four different steps: (1) hypotheses formation in low resolution, (2) hypotheses formation in high resolution, (3) fusion of both resolutions, and (4) network generation. (1) To create highway hypotheses in low resolution, dark and wide lines are extracted (Steger, 1998). The resulting lines are weighted with respect to highway construction parameters (width, length, curvature). Especially variants of the Hough Transform for straight, circular, and elliptical structures help to weight lines according to their evidence being part of a highway. (2) In the high resolution, dark lines and thin bright lines are extracted, i.e., candidates for the individual lanes and the crash barrier in between. To get initial highway hypotheses, parallel dark lines enclosing a bright line are selected. These line aggregation is rated according to highway construction constraints and, in addition, according to the gray value difference of the parallel dark lines. (3) All hypotheses are fused now using a "best-first" strategy. Thereby, hypotheses extracted in both resolutions get the highest weights. (4) Finally, the network is extracted by the graph-based grouping algorithm described in Sect. 3.1.

4 RESULTS

The potential of using context information is demonstrated by two test sites: a rural-industrial test site near Munich, Germany (AeS-1 data) and a 11 km x 7,5 km extended rural test site in South Germany, Ehingen (E-SAR data), both X-band data. A quantitative evaluation of the results according to the evaluation scheme in (Wiedemann and Ebner, 2000) has been carried out with manually plotted reference data. As summarized in Table 1 and Table 2, by means of quality measures for completeness, correctness, and geometrical accuracy the extraction results are evaluated with and without introducing context information. The evaluation shows that the results are relatively complete, especially for main roads (> 93 %). In both test sites the completeness and correctness could be improved by using context information.





(d)

Figure 4: Extraction results (a) SAR image (b) Extraction result without context (c) Extraction result with local context objects (d) Introduced local context objects: vehicle (line), trees and junctions (linking point)

	AeS-1	AeS-1 with context	
Completeness	66.7 %	69.7 %	
highways	63.8 %	64.1 %	
main roads	94.9 %	95.5 %	
secondary roads	64.9 %	71.3 %	
Correctness	71.8%	72.8 %	
RMS	2.2 m	2.2 m	

Table 1: Evaluation of extraction results for Munich

	without	with	with local and
		local	global context
Completeness	84.6 %	85.3 %	88.5 %
main roads	93.9 %	96.9 %	97.2 %
secondary roads	81.3 %	81.2 %	85.4 %
Correctness	73.6%	73.7 %	73.6 %
RMS	2.2 m	2.1 m	2.1 m

Table 2: Evaluation of extraction results for Ehingen

4.1 Results for context objects

In the Munich test site more secondary roads have been extracted by the use of local context objects, especially due to the introduction of bridges. For highways, only a small improvement is reached. Obviously, introducing a traffic sign as a short line segment is not sufficient. To cope with disturbances caused by reflections at metallic structures, a feedback loop to the SAR processing would be necessary, e.g., a specialized technique to suppress the side lopes.

In the case of the Ehingen test site some gaps in the road network could be closed by the aid of individual trees as potential road segments. As depicted in Figure 4 one small gap in the upper left part could be closed. The central gap isn't totally caused by local context objects. Apart of layover of a large tree and a moving vehicle, the low contrast in between seems responsible for the missing extraction. Note, that only local gaps are supposed to be closed by local context information.

Another aspect of modeling context is the higher robustness of the extraction. Influences of non-modeled objects are usually tried to be overcome by relaxing some of the parameters involved (e.g., parameters for grouping lines). On one side, this may lead to a more complete result; on the other side, the result is typically less correct since relaxed parameters cause more misdetections. However, when adding information about context objects during the extraction, the amount of gaps is usually less, so that the parameters can be set much more restrictives.

4.2 Results for context regions

By introducing the contour line of urban areas the algorithm can start the network generation with this segments. Usually, roads nearby urban areas are more influenced by adjacent buildings or vegetation. That is the reason why these road segments are often missing in a conventional extraction. In Figure 4.1 the improvement by using global context is shown. Regarding the left village, two more outgoing branches could be extracted. Furthermore, the contour line might be used as basis to connect loose road parts to a topological correct road network. (To avoid confusion, the two lines running downwards from the village are just ways and therefore not part of the reference data (Figure 5(b)).)

4.3 Results for highways

We applied the extraction system to some test sites which contain highways. The results for a test site north of Karlsruhe are



(a) Ehingen, E-SAR, X-HH amplitude image



(b) Reference data



(c) Road extaction result with local context objects



(d) Road extaction result with local and global context information

Figure 5: Road extaction result with context information



Figure 6: Highway extraction results for Karlsruhe

depicted in Figure 6(b). The left highway (1) has been extracted completely. In the upper part, the crash barrier is clearly visible and the high-resolution lines deliver good candidates for the highway. In the lower part, the highway is partly occluded by vegetation (shadow), as is also the left part of highway (2). Here, the lines extracted at the lower resolution provide essential hypotheses, so that the extraction was successful for most parts of highway (2). The gaps in the extraction of highway (2) are caused by bridges. Here, an introduction of context information as shown above might be useful. Segment (3) is a false alarm.

5 CONCLUSION

An approach for automatic road extraction from SAR imagery was presented and optimized. First, we showed that the introduction of explicitly modeled context objects helps to overcome many local disturbances. Second, the use of global context by introducing the outline of urban areas as seed points for rural roads improved the completeness of the extracted road network and the topological correctness of the network. Third, we modeled and outlined an extraction scheme for highways. Both, model and extraction rely on multiple scales, which makes the results more robust compared to single-scale approaches.

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