AUTOMATIC ROAD EXTRACTION FROM IRS SATELLITE IMAGES IN AGRICULTURAL AND DESERT AREAS

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ABSTRACT

The appearance of roads in northern Africa differs from that of roads, e.g., in central Europe, which most of the approaches for automated road extraction in literature focus on. In this paper we propose a road model for areas with different road appearance in IRS satellite image data with a panchromatic resolution of 5 m and 20 m multispectral resolution. We model areas where water makes agriculture possible on one hand, and areas dominated by the desert and dry mountainous areas on the other hand.
In the desert and mountainous areas paved roads appear as more or less distinct lines and the Steger line extraction algorithm can be used to extract roads in combination with global grouping. In mountainous areas detected, e.g., in a DEM, much larger curvatures are expected to occur than in the desert. In agricultural areas, on which we focus in this paper, roads often do not appear as distinct lines. Borders of the fields represented by edges in the image and the knowledge that these borders can be collinearly grouped, possibly together with lines, into longer linear structures are used to construct road sections. To close gaps, pairs of lines or edges are connected by ziplock snakes. To verify these road sections, the paths of the snakes are evaluated using the line strength and the gradient image. The verified road sections are finally globally grouped using the knowledge that roads construct a network between important points. Gaps which have a high impact on the network topology are closed if evidence supporting this is found in the image. Results show the validity of the approach.

1 INTRODUCTION

For the road network in regions consisting in larger parts of desert or dry mountainous areas, e.g., in northern Africa, there is either no digital data available, or it is often very imprecise and not up to date, i.e., incomplete, or even wrong. Because of the large areas to be mapped, it is important to use highly automated means as well as cheap and readily available data. IRS-1C/D (Indian Remote Sensing Satellite) data with a ground resolution of about 5 m in the panchromatic and about 20 m in red, green, and NIR (near infrared) is a good choice for this. We use pan-sharpened images.

The appearance of roads in these regions differs from that of roads, e.g., in central Europe, which most of the approaches for automated road extraction in literature focus on. In the following we give a short overview over related work, focusing on contributions which employ similar data or similar techniques, e.g., snakes, as our approach.

One of the first approaches to automatic road extraction is (Fischler et al., 1981), where two types of operators are combined: the type I operator is very reliable but will not find all features of interest, whereas the type II operator extracts almost all features of interest, but with a large error rate. Starting with the reliable type I road parts, gaps are bridged based on the type II results employing a search algorithm termed F^*. (Wiedemann et al., 1998) extract and evaluate road networks from MOMS-2P satellite imagery with a resolution similar to IRS employing global grouping. The basis of this approach is the Steger line operator (Steger, 1998). The use of snakes for the detection of changes in road databases in SPOT and Landsat satellite imagery is demonstrated in (Klang, 1998). (Péteri and Ranchin, 2003) employ a multiresolution snake based on a wavelet transformed image to update urban roads based on given unprecise road data. In (Laptev et al., 2000) linear scale space and ziplock-snakes are used for the extraction of roads from high resolution aerial imagery. (Dal Poz and do Vale, 2003) propose a semi-automated approach for the extraction of roads from medium and high resolution images based on dynamic programming. Active testing for the tracking of roads in satellite images is introduced by (Geman and Jedynak, 1996). A semi-automated system for road extraction based on dynamic programming and least squares B-spline (LSB)-snakes is proposed by (Grün and Li, 1997). The automatic completion of road networks based on the generation and verification of link hypotheses given in (Wiedemann and Ebner, 2000). (Wallace et al., 2001) present an approach designed for a wide variety of imagery. It is based on an object-oriented database which allows the modeling and utilization of relations between roads as well as other objects. Road extraction using statistical modeling in the form of point processes and Reversible Jump Markov Chain Monte Carlo is proposed by (Stoica et al., 2004).

Our approach makes use of the 5 m panchromatic resolution as well as the multi spectral information of IRS. It is designed for the extraction of roads in mostly agricultural as well as in arid areas, the latter also comprising mountainous regions. Section 2 describes model and strategy. In Section 3 the individual steps of the extraction process, namely line / edge extraction, generation of connection hypotheses, verification of connection hypotheses, and global grouping are detailed. Section 4 presents experimental results showing the validity of the approach. An outlook concludes the paper.

Figure 1: Sample images from mountainous (left) and desert areas (right)

2 MODEL AND STRATEGY

Due to large differences in the appearance of roads in different areas in north Africa a single model for automatic road extraction is insufficient. We distinguish three areas: agricultural, mountainous, and desert. The characteristics of roads in IRS satellite images in these areas can be described as follows (cf. fig. 1 and 2):

In *mountainous areas* roads are strongly affected by the topography. Roads often turn with a large curvature or even with sharp bends. In the images the roads are mostly represented as bright and only seldom as dark lines.

In *desert areas* roads mostly appear as bright or dark lines with few disturbing objects. The distinction from other linear objects, e.g., pipelines, is often difficult.

In *agricultural areas* roads appear as elongated structures. They often have no bar-shaped line profile in the images, but can be seen indirectly as collinear edges of field borders.

A distinction to what type of area a region belongs can be done mostly automatically based on a Digital Terrain Model (DTM) and the image data itself. Agricultural areas show high intensities in the near infrared channel, mountainous areas are characterized by extended steep slopes in the DTM, and desert areas consist of homogeneous surfaces with low intensities in the near infrared.

Road extraction in mountainous and desert areas starts by extracting lines with the Steger extractor (Steger, 1998). All spectral channels are used independently. The resulting sub-pixel lines are evaluated and fused. In mountainous areas there is no limitation in curvature, whereas in desert areas only linear features with a small curvature are accepted. The verified and fused lines are globally grouped into the road network. A detailed description of the approach is given in (Wiedemann et al., 1998).

The extraction of roads in agricultural areas is much more challenging than in the other two areas. Here, roads not always appear as lines (cf. fig. 2) because they run in many cases along field borders. This means that the borders of the fields often indirectly represent the path of the road. On the other hand, these roads usually form elongated collinear or curvilinear structures with small curvature, i.e., they can be approximated by linear structures. Borders of fields means that there is a more or less strong grey value gradient perpendicular to the road direction. The proposed approach uses these characteristics to construct road sections. To employ as much information as possible, both lines and edges are used to form possible road connections. A detailed description of the extraction is given in the next section.

Figure 2: Sample image from an agricultural area. The white rectangle shows the part used in figures 4 and 6.

3 ROAD EXTRACTION AS COLLINEAR FEATURES

Our goal is to group roads appearing as lines and edges of the field borders into longer linear structures and by this means recognize and delineate the roads. We start with the extraction of lines and edges (cf. fig. 3 and 5), both termed linear features for the remainder of this paper. From these features connection hypotheses are constructed and evaluated. The best path for the connection is obtained by optimizing a ziplock snake between the two adjacent endpoints of the linear features. The final road network is obtained by globally grouping the road sections.

3.1 Extraction of Linear Features

The extraction of the linear features is performed with the Steger sub-pixel line- and edge extractor. The extracted features are split into segments with a curvature below a given threshold. This is done for all image channels independently. In a following step the resulting lines and edges from all image channels are fused to single data sets. From these data sets connections are constructed. Figure 4 shows results of line and edge extraction.

3.2 Construction of Connections

Connections consist of elongated features with a small curvature. Two linear features are used to construct a connection if they satisfy the following conditions:

- the linear features have to be collinear ($\mu_{C_{1,2}}$)
- the linear feature and their straight connection must be collinear (μ_{C_3})

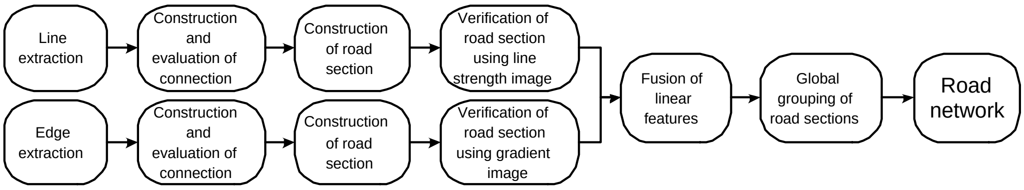

Figure 3: Workflow of road extraction using collinear features

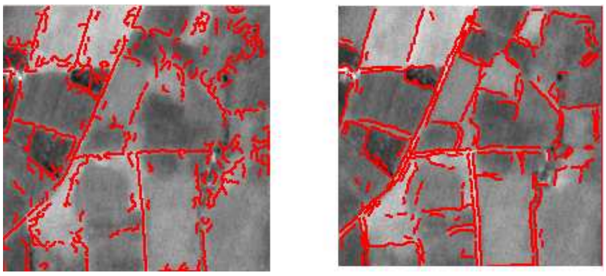

Figure 4: Extracted lines (left) and edges (right). The original image is given in figure 2.

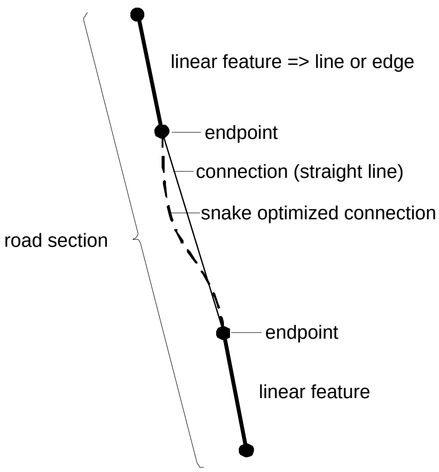

Figure 5: Road section, consisting of linear features and a snake optimized connection.

- the linear features must have a minimum length $(\mu_{L_{1,2}})$
- there is a minimum and maximum length for the connection (μ_{L_3})

The evaluation parameters μ are not simply thresholded, but they are interpreted as fuzzy values. The fuzzy variables are combined into one evaluation value (μ_{CON}) with the Fuzzy AND operator (1) (Zadeh, 1989).

$$\begin{aligned}\mu_{CON} &= \mu_{C_1} \wedge \mu_{C_2} \wedge \mu_{C_3} \wedge \mu_{L_1} \wedge \mu_{L_2} \wedge \mu_{L_3} \\ &= \mathbf{MIN}(\mu_{C_1}, \mu_{C_2}, \mu_{C_3}, \mu_{L_1}, \mu_{L_2}, \mu_{L_3}) \end{aligned} \quad (1)$$

Connections with a combined evaluation value above a given threshold serve as basis for the construction of road sections.

3.3 Construction of Road Sections

To determine the actual path of the connection, the two adjacent endpoints of the linear features are used as start points for a ziplock snake (cf. fig. 5).

Snakes, also called Active Contour Models, were introduced by (Kass et al., 1988). A snake is described by geometric (E_{int}) and photometric (E_{ext}) energies, with $E_{snake} = E_{int} + E_{ext}$. The goal is to minimize the energy by varying the path of the snake. Due to the photometric energy the snake is pulled to image features, whereas the geometric energy usually controls the tension and rigidity of the snake.

(Neuenschwander et al., 1995) crafted the term ”ziplock snake”, for which the optimization is performed from both sides inwards. The advantages of this approach when using it for bridging gaps in roads are that the given information about the endpoints is exploited well, while local minima, which arise especially in the middle of the gap due to a bad prediction of the road path, are avoided (Laptev et al., 2000). During the optimization process the active parts of the snake, where the image information is exploited, move step by step from both sides towards the center.

As roads can appear as bright lines and image edges, a line strength and a gradient image, respectively, are used as photometric energy. The line strength image is calculated in form of the maximum negative eigenvalue of the Hessian Matrix (2) for each pixel.

$$H(x,y) = \begin{bmatrix} g_{xx} & g_{xy} \\ g_{xy} & g_{yy} \end{bmatrix} \quad (2)$$

Here g_{xx}, g_{yy} and g_{xy}, represent the second derivatives of the Gaussian smoothed image, with $\sigma = 2.0$, in x and y direction,

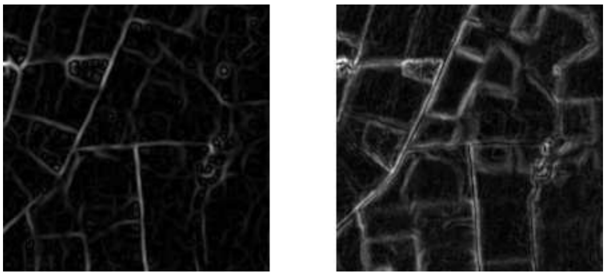

Figure 6: (Left) Line strength image representing the absolute values of the maximum negative eigenvalues of the Hessian matrix. (Right) Gradient image representing the absolute values of the sobel filter mask. The original image is given in figure 2.

as well as the mixed derivative. Large negative eigenvalues are obtained for a bright line, whereas large positive eigenvalues correspond to dark lines. We note that also point features lead to large positive as well as negative eigenvalues, but they do not disturb our procedure. As experience shows, that most of the roads appear as bright lines in the images, only the maximum negative eigenvalues are used. To take into account the information of all image channels, the eigenvalues are calculated for every image channel and the maximum of the absolute value for every pixel is written into the line strength image. An example is shown in figure 6, left.

Also the maximum gradient image is generated using all image channels. For every image channel a Sobel image is calculated using the medium absolute values. The maximum value for every pixel of these Sobel images is taken for the maximum gradient image (cf. fig. 6, right). By employing the line strength and the gradient image as input data for our snake based approach we focus on the features we are interested in, i.e., bar-shaped roads and field borders.

3.4 Verification of Road Sections

A disadvantage of snakes is that they will minimize their energy in any case, even if there are no meaningful image features available. This leads to the necessity to verify the result by examining the path of the resulting snake. In our approach the verification of the snake is synonymous with the verification of the road sections. As criteria for the correctness the line or edge strength along the path of the snake is used. A section is verified only if there is enough evidence for a linear feature along the path.

A grey value profile in the line strength or gradient image perpendicular to the snake direction is calculated for every snake point. To evaluate the quality of a single point, the profile is first smoothed with a Gaussian kernel. Then, the maximum value along the profile and the position of the maximum are calculated. For a valid point the maximum should be close to the center of the profile and the second derivative along the profile at the maximum point should be significantly smaller than zero. To accept a road section, the percentage of valid points needs to be larger than a given threshold.

3.5 Global Grouping

The result of the previous step are individual road sections. To construct a network, road sections are grouped into larger structures. As road sections may result from either line or edge features they need to be fused first into linear features. To do so, the road sections are evaluated using the quality measure generated by the previous verification. Because road sections resulting from lines are more reliable, they are given a higher weight than those obtained from edges. The result are the road sections with the highest evaluation value.

An important property of a road network is, that most points on the network can be reached from all other points along an optimal path with a minimum detour. To make use of this property, we generate link hypotheses according to (Wiedemann and Ebner, 2000). The distance between pairs of points within the network is calculated along the existing network and along a hypothetical optimal path, for which the Euclidean distance is used. To form so-called preliminary link hypotheses, a detour factor is calculated as follows:

$$detour\ factor = \frac{network\ distance}{optimal\ distance} \tag{3}$$

The link hypotheses are checked starting with the hypotheses with the largest detour factor. If a link hypotheses is accepted, the new connection is inserted into the road network. Due to changes in the network, the generation of link hypotheses has to be repeated. This is iterated until no more new link hypotheses are generated. The result of the global grouping is the final road network.

4 EXPERIMENTAL RESULTS

For the validation of the proposed approach pan-sharpened IRS-1C/D satellite images for a test site in northern Africa were used. The images were selected in a way that they comprise different road types in agricultural as well as in mountainous test areas. We have not yet generated reference data for a quantitative evaluation, therefore, the validation is done just qualitatively by visual inspection.

Figure 7 shows the results obtained for the first image sample shown in figure 2. The network extracted for this example shows, that in agricultural areas not only main roads can be extracted, but also smaller roads that connect, e.g., individual farms, for instance on the right side of figure 7. One difficulty here is the distinction between roads and paths that follow the borders of a field.

The second example (fig. 8 and 9) shows a complex road network. Several small villages are connected by roads of different importance. Most of the roads outside the villages were correctly extracted. As the approach is developed for roads in agricultural areas, the streets inside the villages could, as was to be expected, mostly not be extracted. Worth to mention is the small number of false positives.

The third example (fig. 10 and 11) shows a road passing through a mountainous area. For this example the approach of (Wiedemann et al., 1998) was used. No limitation for the maximal allowed curvature was set.

Figure 7: Result of road extraction in agricultural area

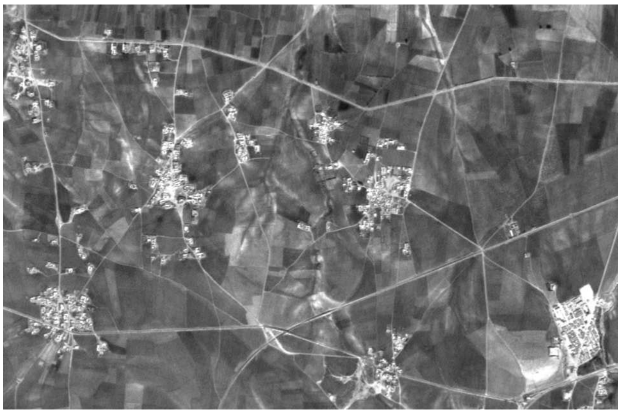

Figure 8: Image data

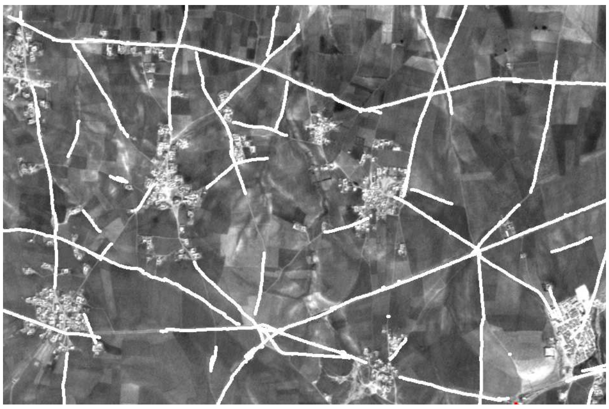

Figure 9: Result of road extraction in agricultural area

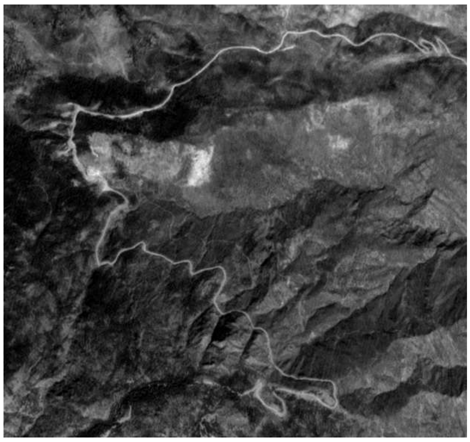

Figure 10: Image data

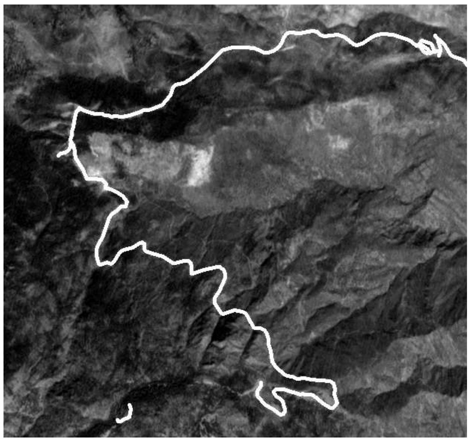

Figure 11: Result of road extraction in mountainous area

5 CONCLUSIONS

We have proposed a new approach for the extraction of roads in agricultural areas in 5 m resolution IRS data. The approach is based on the fact, that roads in these areas are often not directly visible, but they run along field borders and form elongated structures. Starting with the extraction of linear features, connection hypotheses are generated. The evaluated connections are optimized by means of ziplock snakes. The verification of the generated road sections is performed by checking the path of the snake. Using the verified road sections a road network is constructed by means of global grouping. Experiments have shown, that not only the main roads but also smaller roads can be extracted from the used IRS imagery. By means of the approach of (Wiedemann et al., 1998) we are also able to extract roads in desert and mountainous areas from IRS data.

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