FUZZY-CLASSIFICATION AND ZIPLOCK SNAKES FOR ROAD EXTRACTION FROM IKONOS IMAGES

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ABSTRACT

In this paper we propose an approach for automatic road extraction from pan-sharpened IKONOS images which makes use of the 1 m resolution as well as the multispectral information. The approach consists of three main steps and can be seen as an add-on to the approach of *Wiedemann (2001)*. In the first step, training areas for a multispectral classification are extracted in all channels using the Steger differential geometric line operator. Additionally, there have to be parallel edges with a homogeneous area between them within a neighborhood of the extracted lines. In the second step, the training areas are used for a fuzzy multispectral classification. With it, additional road pixels are extracted. The number of misclassifications is minimized by means of a rank filter. In the final step, gaps in the preliminary road network generated with the approach of *Wiedemann (2001)* are closed by means of ziplock line snakes employing the classification results. Examples show the validity of the approach.

1. INTRODUCTION

Most approaches for automatic road extraction deal with panchromatic aerial imagery with resolutions better than 0.5 m or satellite imagery with resolutions worse than 2 m. The resolution of the new high resolution commercial sensors lies with 1 m for IKONOS and 0.6 m for Quickbird in-between, but they additionally provide four spectral channels. A big advantage of this kind of imagery compared to aerial imagery is their almost worldwide availability without the need to actually visit a region. This makes the data very interesting, e.g., for the generation of infrastructural information for military or humanitarian planning in areas of crisis, where often a quick response is a must.

There has been a large amount of related work on road extraction from aerial and satellite imagery in recent years. Here we focus on work which employs similar data or similar techniques, e.g., snakes, as our work. *Wiedemann et al. (1998)* deal with the extraction and evaluation of road networks from MOMS-2P satellite imagery with a resolution of 6 m. The basis of this approach is the Steger line operator *(Steger 1998)*. *Baumgartner et al (1999)* use multiple scales, grouping, and context for automatic extraction of roads from high resolution images. In *(Laptev et al. 2000)* scale-space and snakes are used for the extraction of roads from high resolution aerial imagery. A semi-automatic system for road extraction based on least-squares B-splines (LSB)-snakes and dynamic programming is proposed by *Grün and Li (1997)*. *(Wallace et al. 2001)* present an approach designed to be used on a wide variety of imagery. It is based on an object-oriented database which allows the modeling and utilization of relations between different roads as well as roads and other objects. *(Hu and Tao 2002)* extract main roads from high resolution satellite imagery based on hierarchical analysis, perceptual grouping, and least-square template matching. *Dal Poz and do Val (2003)* propose a semi-automatic approach for road extraction from medium and high resolution images based on dynamic programming. *Mena and Malpica (2003)* are using the Dempster-Shafer theory of evidence for the fusion of color and texture measures for automatic road extraction. There are few papers about road extraction from IKONOS imagery. *(Dial et al. 2001)* gives an overview over the properties of the sensor and presents a road extraction approach using the multispectral features of the imagery. A system for road extraction from IKONOS multispectral imagery based on fuzzy logic is proposed by *Amini et al. (2002)*. Also *Mena and Malpica (2003)* use IKONOS imagery. *Peteri and Ranchin (2003)* employ a multiresolution snake for the extraction of urban road networks from IKONOS and Quickbird imagery given existing but imprecise GIS data.

In this paper we propose an approach for automatic road extraction from pan-sharpened IKONOS images which make use of the 1 m resolution as well as the multispectral information. The system is designed for the automatic extraction of roads in rural and suburban areas. The paper is structured in the following way: Section 2 introduces the data. In Section 3 the three parts of the extraction are detailed: generation of training areas, fuzzy-classification, and building of the road network. Section 4 presents experimental results showing the validity of the approach. A short outlook concludes the paper.

2. IMAGE DATA

The imagery consists of a pan-sharpened IKONOS scene with a resolution of 1 m. It was acquired in September 2000 and covers a mostly rural and hilly region of the Kosovo. We have used the red, green, blue, and near infrared (NIR) channel. Some regions of the scene are deteriorated by haze. This is especially true for the blue channel. The radiometric resolution of 11 bit was not completely exploited as the data was transformed into 8 bit per color to make the handling easier. From the whole scene some representative parts were selected. An overview over the radiometric and geometric properties of IKONOS image data and its potential for automatic object extraction can be found in *(Baltsavias et al. 2001)*.

3. AUTOMATIC ROAD EXTRACTION

From the point of view of this approach, roads are linear objects with a more or less constant width, i.e., with parallel edges. Sections of the road network consist of the same material and therefore show similar radiometric properties in multispectral images. Usually roads have a smooth trajectory. Our system for automatic road extraction is therefore based on the following strategy:

- Training areas are generated in the form of linear objects with parallel edges.
- A classification using these training areas leads to potential road pixels.
- Finally, the gaps in a preliminary road network generated according to *Wiedemann (2001)* are closed by ziplock snakes *(Neuenschwander et al. 1995, Laptev et al. 2000)* based on the classification results.

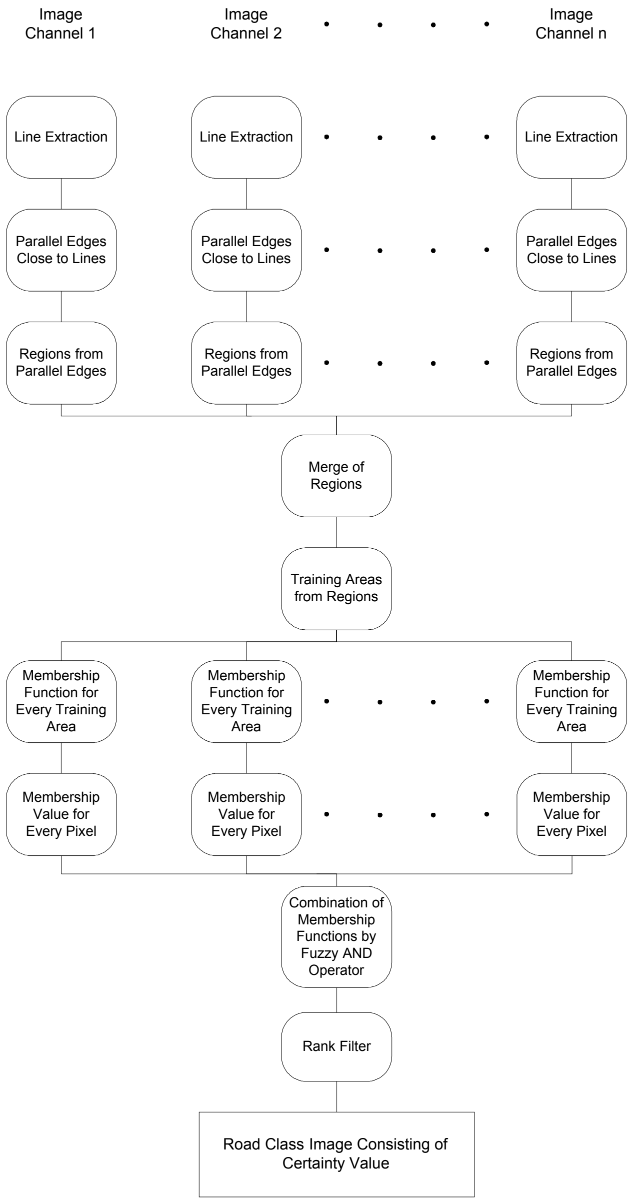
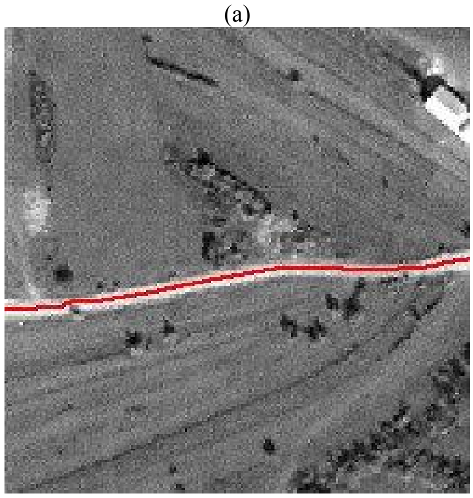


Figure 1: Fuzzy road classification

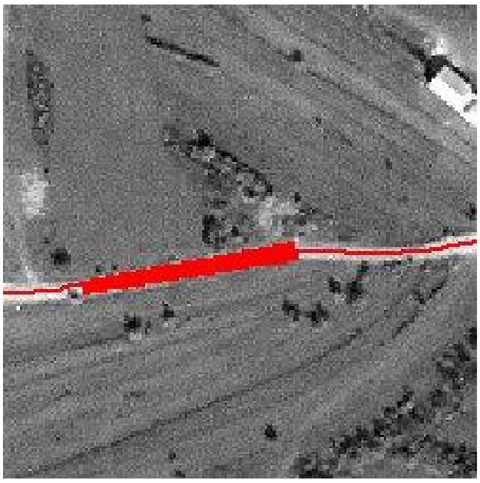
3.1 Generation of Training Areas

For a classification of multispectral imagery it is necessary to know the spectral properties of the class to be detected. To obtain this information, areas which are known to belong to the class, so-called training areas are used.
After line extraction, parallel edges are extracted as an additional evidence in the neighborhood of the line (Fig. 1). The line extraction is carried out using the differential geometric *Steger (1998)* operator. The approach is controlled by parameters specifying the assumed width of the roads and the expected contrast between the road and its neighborhood. The result of the line extraction are polygons with sub-pixel accuracy. Only lines longer than a preset threshold are selected (Fig. 2). Edges are detected in buffers around the lines with a width slightly larger than the expected road width. The edges are checked for parallelism and homogeneity of the grey values in the area between them. From them road hypotheses are generated in all image channels. The road hypotheses of all image channels are merged into road regions. Only road regions larger than a given threshold are accepted (Fig. 2c). Large regions are divided into smaller parts. The resulting regions serve as training areas for the fuzzy classification.

(a)



(b)



(c)

Figure 2: Automatic generation of training areas. (a) Original image (b) Extracted line (c) Training area.

3.2 Fuzzy-Classification

The membership value of a pixel of the road class is calculated by fuzzy *(Zadeh, 1965)* based classification (Fig. 1). Here, the goal is only to determine whether a pixel belongs to the road class or not, i.e., no distinction is made between different object classes. For each of the training areas the mean (m) and standard deviation (σ) of the grey values are calculated. A Gaussian membership function $\mu(x) = \exp\left\{\frac{-(x-m)^2}{2\sigma^2}\right\}$

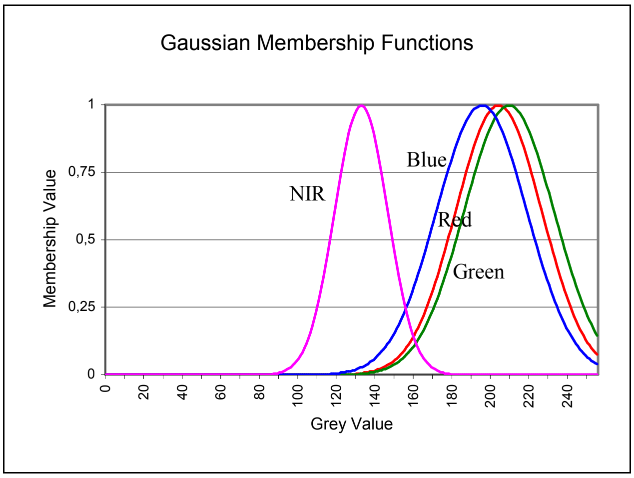
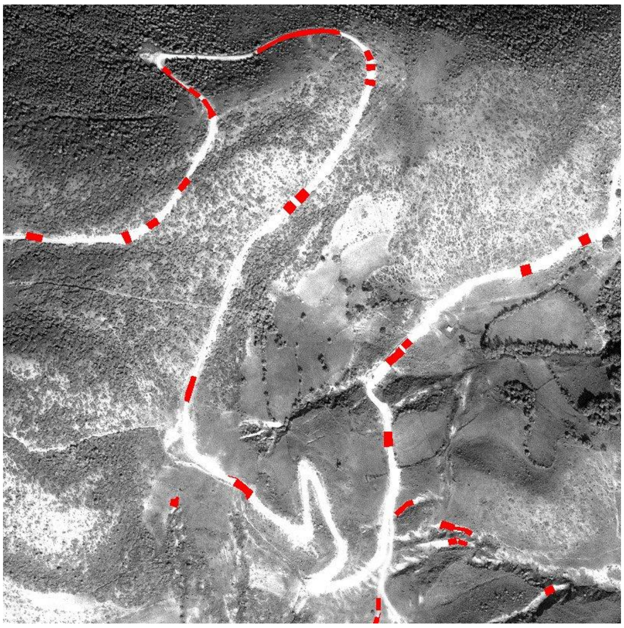


Figure 3: Gaussian membership function for one training area

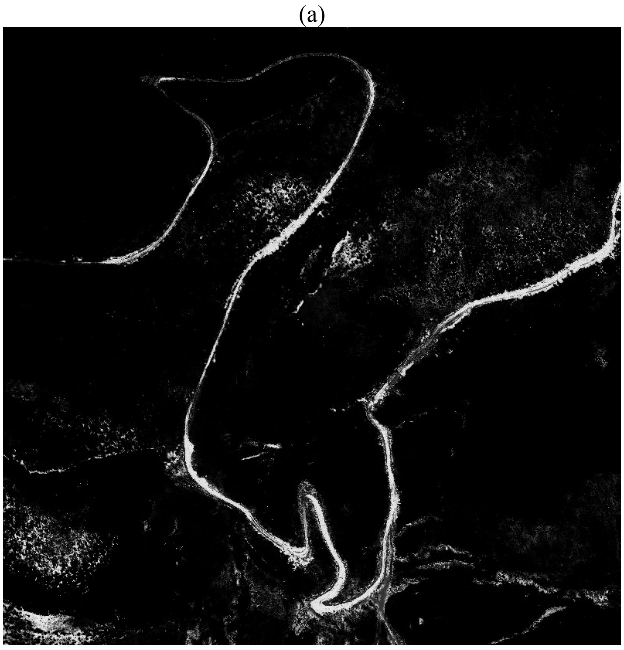
(Fig. 3) is build from these parameters for each image channel. The membership value for every pixel is calculated for each image channel. By means of the fuzzy AND operator

$$\mu_R(x_i) = \mu_1(x_i) \wedge \mu_2(x_i) \wedge \cdots \wedge \mu_n(x_i) = MIN\ [\mu_1(x_i), \mu_2(x_i), \cdots, \mu_n(x_i)]$$

the final membership value (μ_R) for every training area for every pixel is computed and stored in a membership array. To be more robust against outliers, a rank filter is applied to the array to cut off a pre-set percentage of values. To avoid cutting off with the rank filter roads with a characteristics, for which only one large training area has been found, has been the reason to divide large regions into smaller parts above. The result of the classification is an intensity image (Fig. 4) representing the certainty of a pixel to be part of the road class.



(a)



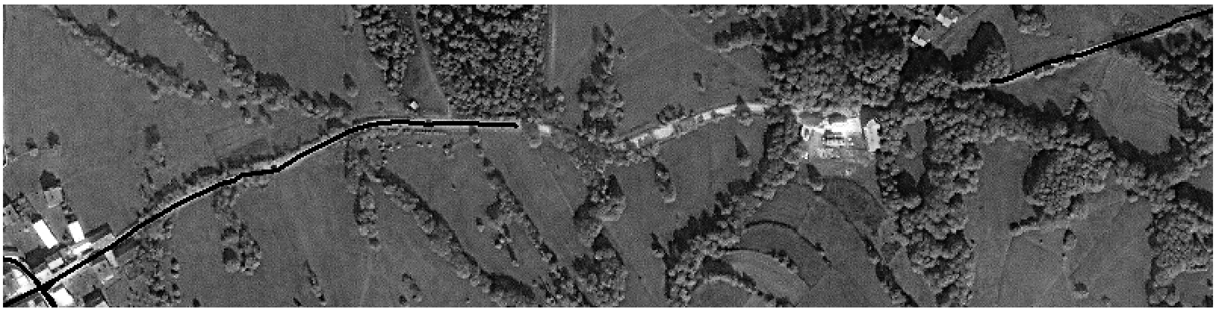
(b)

Figure 4: (a) Image with training areas (b) Road class image

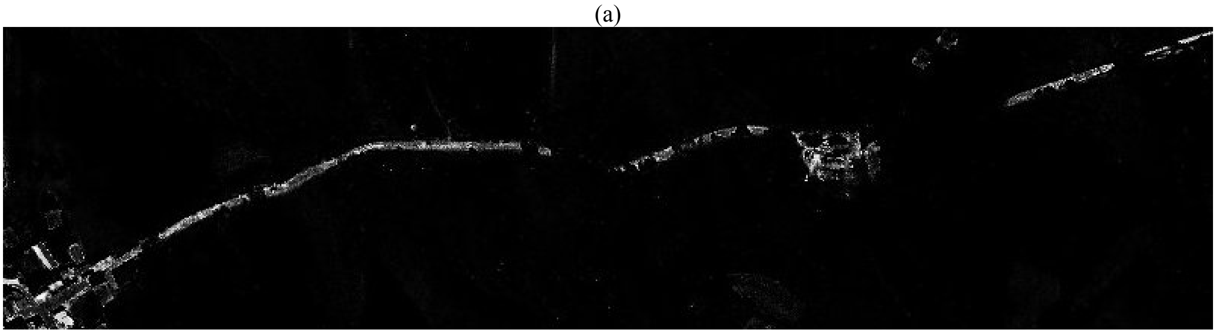
3.3 Generation of the Road Network

The road class image is employed to close gaps in a preliminary network according to *(Wiedemann 2001)*:

- Lines are extracted in all image channels using the *Steger (1998)* operator.
- The quality of each line is measured according to its length, straightness, width, as well as standard deviation of width and grey value.
- Lines from all image channels with a quality better than a given threshold are fused to the preliminary road network.



(a)



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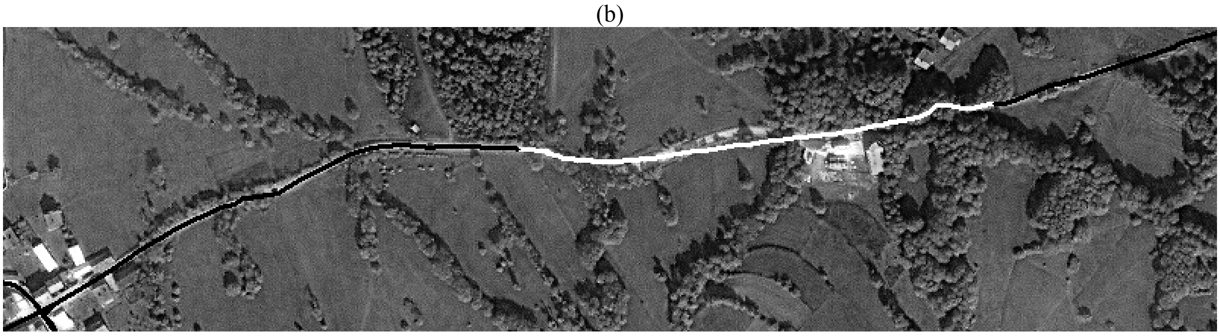
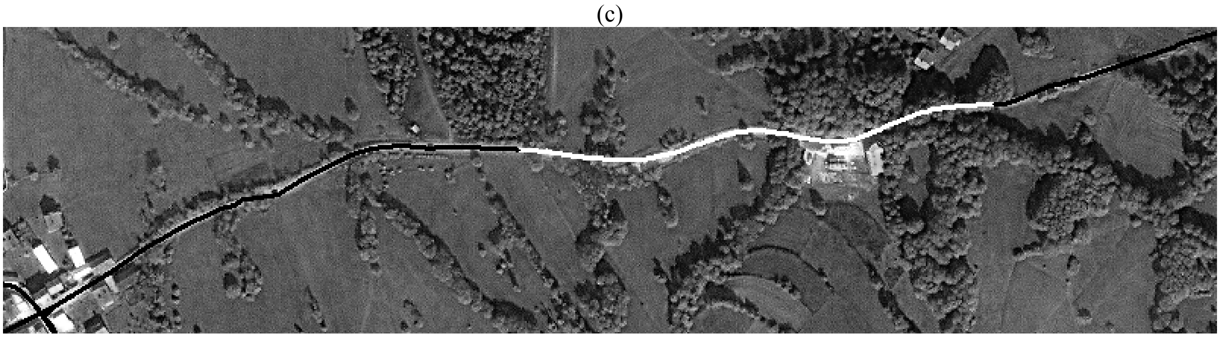


(c)

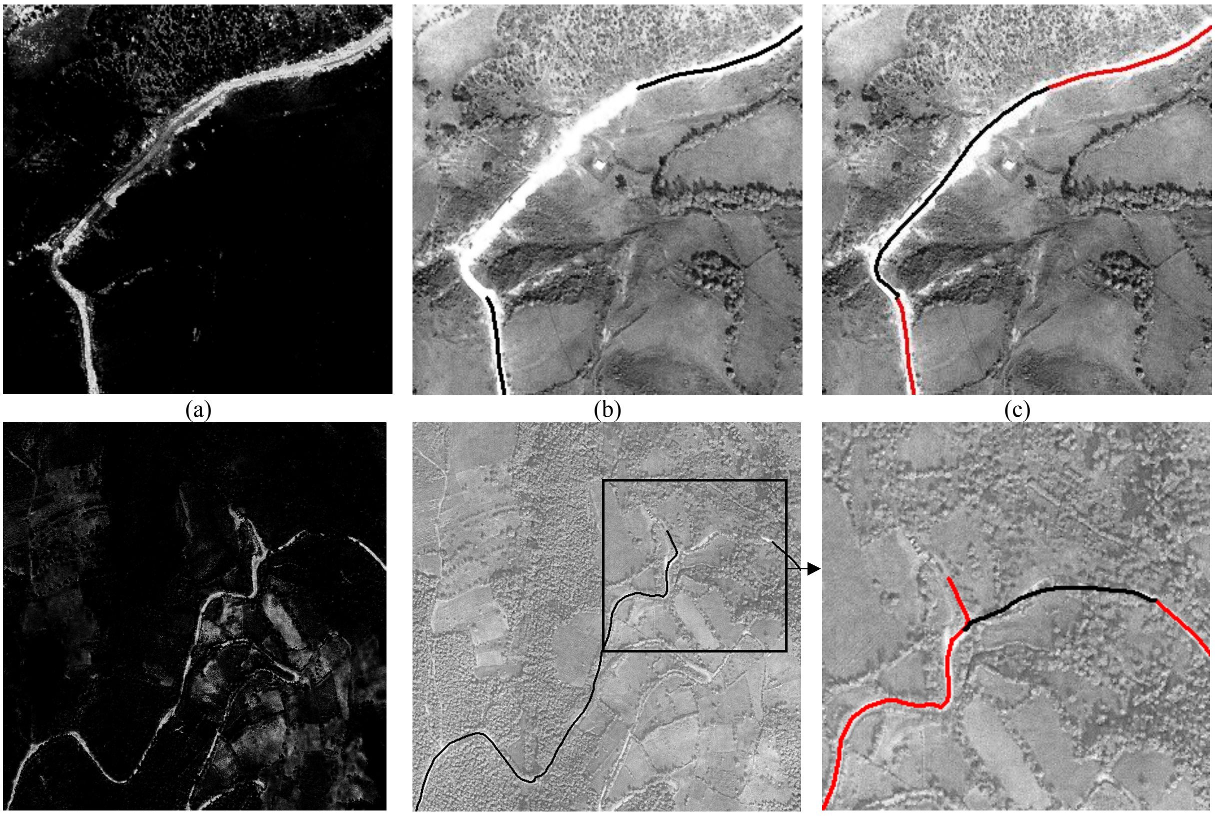


(d)

Figure 5: (a) Preliminary road network (b) Road class image (c) Gap bridged by zip-lock snake using the original image data (d) Gap bridged by zip-lock snake employing the road class image.

Employing the approach proposed in (*Wiedemann 1999)*, link hypotheses are generated for gaps in the preliminary road network. To close the gaps and verify the link hypotheses, ziplock snakes are used.

Snakes, also called Active Contour Models, were introduced by *Kass et al. (1987)*. A snake is described by geometric (E_{int}) and photometric (E_{ext}) energies, with $E_{Snake} = E_{ext} + E_{\mathrm{int}}$. The goal is to minimize the energy by varying the path of the snake. Due to the photometric energy the snake is being pulled to image features, whereas the geometric energy controls the tension and rigidity of the snake. *Neuenschwander et al. (1995)* crafted the so called ziplock snake, for which the optimization is performed from both sides inwards like a ziplock. The advantage of this approach when using it for bridging gaps in roads is that the given information about the endpoints is fully exploited, while local minima which can arise especially in the middle of the gap due to a bad prediction of the road path are avoided *(Laptev et al. 2000)*. Practically, during the optimization process the active parts of the snake, where the image information is exploited, move step by step to the center.



(a) (b) (c)

(d) (e) (f)

Figure 6: (a)(e) Road class image (b)(e) road extraction result without bridging gaps (c)(f) bridging gap by zip-lock snake employing the road class image.

Here, not the original image information is employed but the road class image, making the extraction more reliable. A ziplock snake with the image energy in form of a line is initialized at the two endpoints of a hypothesized connection and then optimized (Fig. 5). To verify a connection, i.e., to decide if the hypotheses actually corresponds to a road, the profile of the road class image perpendicular to the path of the snake as well as the total image energy along the snake is used.

4. RESULTS

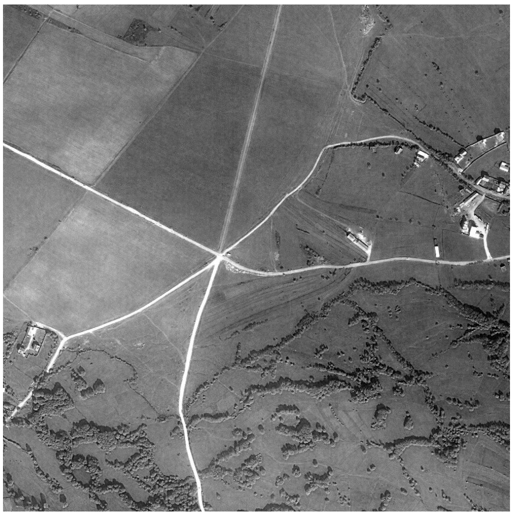
The classification approach has been tested for a variety of road types: rural road with few disturbances by trees, shadows, or buildings (Fig. 7), rural road with some disturbances (Fig. 6), and gravel road in hilly areas with not always clearly defined road edges (Fig. 4).

The potential of the multispectral information provided by the IKONOS sensor can be seen from the road class images (Fig. 4b, 5b, 6a, 6d, and 7b). Pixels belonging to a road are well classified. Due to the use of a rank filter, misclassifications are minimized (Fig. 7), whereas problems occur when the spectral properties in the surrounding of the roads are similar to that of the road (Fig. 4).

Optimizing a ziplock snake based on the road class image is very promising (Fig. 5 and 6). Using the road class image to bridge gaps in the preliminary road network is more robust than employing the original image data as shown in (Fig. 5c and 5d).

5. CONCLUSIONS AND OUTLOOK

In this paper we have presented an approach for the automatic extraction of rural and suburban roads using IKONOS images. From the multispectral image data a road class image was generated based on automatically extracted high reliable training areas. Gaps in a preliminary road network, extracted according to *Wiedemann (2001)*, are bridged using the road class image by means of a ziplock snake. First tests show promising results. Nevertheless the approach has to be tested with a wider variety of images, e.g., Quickbird images or imagery from other regions. Future work will consist of exploring the potential of the road class image for basic road extraction.



(a)

(b)

Figure 7: (a) Original image (b) Road class image

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