Automatic Road Network Extraction from High Resolution Satellite Images

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Abstract*: In this paper we suggest a methodology for automatic road extraction from high resolution satellite imagery, such as IKONOS or Quickbird. While aerial imagery usually contains 3 spectral bands, high resolution satellite images holds 4 spectral bands with a healthier radiometric quality compared to film, but a poorer geometric resolution. Thus, we are using the spectral properties of satellite imagery, a way to reduce the geometric weaknesses and attain results comparable to aerial imagery. Finally, we are using the local as well as global properties of roads. The process of road extraction begins with the extraction of Steger lines. These lines are used as signs for roads to produce training areas for a succeeding automatic managed classification. The results of the classification are used as a supplementary source for the extraction of road candidates. Our innovative verification process for road assumptions makes use of geometric conditions as well as the spectral properties of roads by calculating the road energy from the road class image. From the verified road hypotheses a final road network is created by first connecting small gaps based on a weighted graph and then probing for missing connections in the network by computing local diversion factors. The missing connections are cured by ziplock snakes between pairs of seed points and are then verified. An estimation of the results is done by matching our results with manually extracted reference data representing the strength of the approach.

***Keywords:* Fuzzy classification, Steger lines, Verification process, Ziplock snakes.**

1. INTRODUCTION

The innovation of high resolution satellite imagery such as IKONOS or Quickbird provides new opportunities for the extraction of linear features such as roads. The benefits of this data compared to aerial imagery are the almost worldwide availability and the radiometric resolution of 11 bit in usually 4 spectral bands. The geometric resolution with 1 m for IKONOS and 0.6 m for Quickbird is poorer than for aerial imagery, but for the purpose of road extraction, these are still sufficient.

The worldwide availability of the data makes it possible to yield topographic databases for nearly any region of the earth, for example for military purposes and disaster prevention or relief. At present, information extraction from images is achieved mostly manually, and thus time and cost intensive.

To overcome this restricted access, automatic means are desired. In the field of road extraction most of the existing work was either done for aerial imagery or for satellite imagery with a resolution poorer than 2 m. Our goal is to build up an approach for automatic road extraction for high resolution satellite imagery based on techniques originally invented for aerial as well as average resolution satellite imagery.

There is a lot of related work on road extraction from aerial and satellite imagery. For a general idea we will concentration on recent work which employs similar data or techniques, e.g., classification, building of networks, connecting of gaps, or snakes, as our approach. In [1] two types of operators are combined: the type I operator is very trustworthy but will very likely not obtains all features of our interest, whereas the type II operator obtains almost all features of our interest, but with a possibly maximum error rate. Starting with the type I road parts, gaps are connected based on the type II results employing F* search.

Wiedemann et al., [2] extract and calculate road networks from MOMS-2P satellite imagery with a resolution of about 6 m applying global grouping. The basis of this approach is the Steger line operator [3]. An outline for the extraction of lines and edges for the recognition of roads in SPOT or Landsat imagery is proposed in [4]. The use of snakes for the finding the changes in road databases from SPOT and Landsat satellite imagery is demonstrated in [5]. Wallace et al., [6] proposed an approach designed for a extensive variety of imagery. It is based on an object-oriented database which agrees the modelling and utilization of relations between roads as well as other objects. Recently, road extraction using statistical modelling in the form of point processes and Reversible Jump Markov Chain Monte Carlo was presented by Stoica et al., [7].

A number of papers on road extraction from high resolution satellite imagery, particularly IKONOS. Dial et al., [8] gives an idea about the properties of the IKONOS sensor and introduces a road extraction approach making use of the multispectral features of the imagery. A system for road extraction from multispectral imagery based on fuzzy logic is presented by Amini et al., [9]. Doucette et al., [10] proposed a semi-automatic method that uses a preclassified imagery to sense the roads using the so called" Self Organizing road map" (SORM). In [11] a multi-resolution analysis strategy based on wavelets, road junction finding, and grouping is presented. Mohammadzadeh et al., [12] presented an approach based on fuzzy logic and mathematical morphology.

In this paper we propose a new approach for automatic road extraction from pan-sharpened IKONOS images which makes use of the 1 m panchromatic resolution as well as the multispectral data. It is aimed for the automatic extraction of roads in rural and suburban areas.

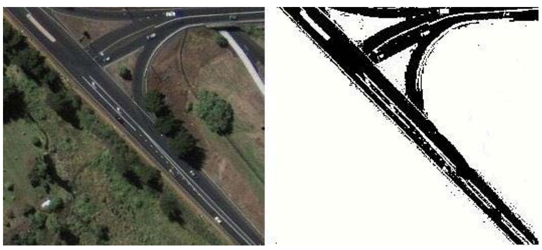
2. CLASSIFICATION

Roads in high resolution satellite imagery mostly relate to elongated regions with a locally non-variant spectral signature. Here, we used a fuzzy classification as presented in [13]. The goal is to determine a membership value for the road class for each pixel. The method consists of two main parts: (1) automatic generation of reliable training areas and (2) fuzzy classification.

Training areas are created from linear features that satisfy the following conditions:

- There exist parallel edges close to each other on both sides of the linear feature.
- The change in the grey value within the region between the parallel edges is little.

Introductory training areas are pulled out separately in every channel of the MSI. They are then fused to produce the final set of training areas, which is required to have a minimum number of road pixels to define the spectral features of the road class.



(a) **(b)**

Fig.1. (a) Original image. (b) Result of classification where the brightness relates to the degree of membership to the road class.

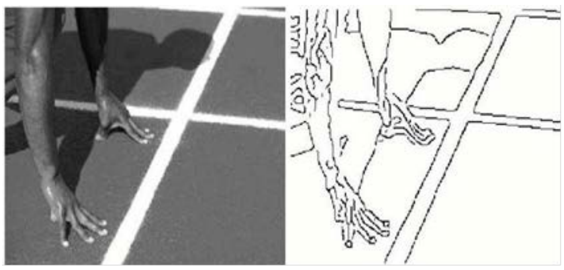
The classification is fuzzy-based. A Gaussian membership function is employed, using the mean and standard deviation of the gray values in each channel, for every training area. Using these functions, merging the results of the single training areas, and finally executing a rank filtering, a final membership value for every pixel to the road class is computed. By this way we can build roads, made of different materials. An example for a so-called "road class image" is presented in Figure 1.

3. ROAD EXTRACTION

The approach for road extraction is presented in this paper stretches [3, 2]. We have followed it for high resolution MSI by adding a new module for the verification of road hypotheses that does not only make use of the geometric constraints, but also the spectral properties of the roads. The extraction policy make use of the local properties of the roads while performing line extraction and generating road hypotheses followed by their verification. Finally, we employ the global properties of roads by creating a road network.

3.1. LINE EXTRACTION

Line extraction is important in calculating the road width. In our system, the line extraction is done automatically at the starting of the tracking process. In our work we have taken an assumption that the roadsides are straight and parallel lines to each other on the both side of the road axis. We need to calculate the distance between the roadsides to figure out the width of the road.
To detect the road edges, the selection of edge detectors is important for the generation of appropriate edge information. The Sobel, Robert and Canny detectors are commonly used edge detectors. Sobel cannot provide satisfactory results because some redundant edges within the roads can also be detected, but cannot be removed due to the fixed parameters set in the Sobel.



(a) **(b)**

Fig.2. (a) Original image. (b) Edge detection using Canny edge detector.

The Robert edge detector can easily achieve a clear and proper edge image from a QuickBird Pan image. However, some detailed edges in indistinct edge areas cannot be detected. The Canny edge detection algorithm is known as an optimal edge detector, which needs to adjust two thresholds and a standard deviation of a Gaussian smooth mask to yield a proper result. So we have applied the Canny edge detector. The main reason to use the Canny edge detector is, the edges from the Canny detector are thin. But, edges in blurred areas can be clearly delineated. That means it provides a good results while dealing with low resolution images.

3.2. ROAD HYPOTHESIS VERIFICATION

Apart from the similarity of the grey value along the road, the valuation of the road hypotheses is completed in [2] only based on geometric considerations. We have not applied spectral properties. To use as much knowledge as possible for the verification of road hypotheses, we established a new method for calculating road. Mostly, we calculate fuzzy values [14] for the following parameters:

- length $\boldsymbol{\mu_l}$
- average width $\boldsymbol{\mu_w}$
- road energy, i.e., average membership $\boldsymbol{\mu_e}$ value of the road hypotheses.

Figure 2 represents the conditions for the calculation of road hypotheses and the linear membership functions applied for the computation of the equivalent fuzzy values. The individual fuzzy values are united into one final weight $\boldsymbol{\mu_r}$ for each line with the fuzzy AND operator using the following equation.

The road hypotheses are considered to be verified and are used for the following generation of a road network, if the final weight ¹R is above a given threshold.

3.3. ROAD NETWORK CREATION

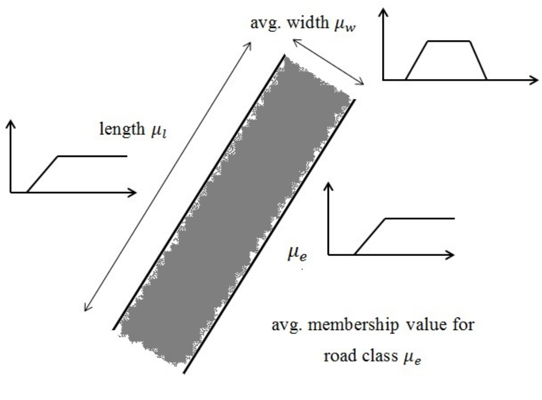


Fig.3. Criteria for the assessment of road hypotheses together with the membership functions for the evaluation of the corresponding fuzzy-values.

For the verification, the individual spectral channels are observed independently resulting to a solid redundancy. To create a consistent set of roads, the results from the different channels are merged excluding redundant roads in the same way as in [15]. Starting from the merged road, a network is created in following two steps:

First, lasting minor gaps are removed by using a weighted graph technique. The missing connections in the graph are spotted by detecting the best path between pairs of seed points using the Dijkstra algorithm and computing weights for the probable connection. A gap is removed if the connection is portion of an optimum path, without using the image information as in [2].

Second, bigger gaps are removed using the method of Wiedemann [16] improved with a new module suggested by Bacher and Mayer [13] for the verification of possible connections. Probable gaps are sensed using the property of road network that most points can be contacted from all other points with minimum detour. To use of this property, link hypotheses are made. The distance of adjacent points is estimated once along the network and once along the assumed optimal path, i.e., if nothing else is called Euclidean distance. From these distances a detour factor is figured using following equation.

$$\boldsymbol{\mu_r = \mu_l \wedge \mu_w \wedge \mu_e = \min(\mu_l, \mu_w, \mu_e)} \qquad \textbf{(1)}$$

The link assumptions are tested with the new module, described below, beginning with the assumptions with the biggest detour factor. If the link assumption is accepted, the new connection is introduced into the road network. Due to changes in the network, the generation of link assumption has to be repeated. This is repeated until no more new link assumptions can be created. The result of this global grouping step is final road network.

The module for the verification of link assumption begins with the two end points of the potential connection. The aim is to measure the optimal path between these points with respect to the geometric and radiometric properties of roads and make use of it to confirm or discard the link assumptions. To resolve the path, a ziplock snake [17] is enhanced between the two end points using the image information of the road class image (cf. Fig. 4). To confirm or discard a link assumption, i.e., to select if the assumption actually relates to a road, a grey value profile perpendicular to the snake direction is considered for every snake point in the road class image. When estimating the quality of a single point, the profile is first smoothed using a Gaussian filter. Then, the maximum value along the profile and the position are estimated. For a valid point the maximum should be near to the centre of the profile and the second derivative along the profile at the maximum point should be lesser than zero. A link assumption is adapted if the average estimation value of all snake points is exceeding a given threshold.

4. EXPERIMENTS

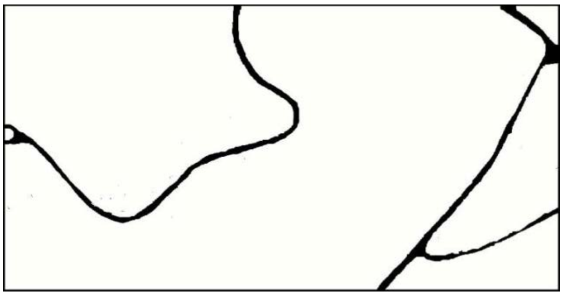
The projected approach was verified on a large number of images. Here we introduce results for IKONOS image. To evaluate the results, the parameters – Completeness, Correctness and Root Mean Square Error (RMS) – from [18] were utilized.

The results for the verified area (Fig. 4) show that the number of false positives is less when benchmarked with the maximum reference where all roads together with the small access ways are convoluted. On the contrary, one can perceive from benchmarking with the minimum reference that above 90 % of the roads are extracted with a symmetrical accuracy of about 1 m.

Moreover, the results are presented in Figure 4, for the tested area, we have developed only one reference set, similar to the maximum reference. The results represents, that most of the main roads in processed image were properly extracted. Our approach is capable to handle abrupt sharp bends or roads built up of different materials.

(a)

(b)



(c)

Fig.4. (a) Satellite image, of size 1150 x 570 pixels; (b) extracted road image; (c) reference data – black minimum reference, black + grey maximum reference;

The results in the urban areas are not very satisfying, providing a clear indication why the approach is planned for open areas. The number of false positives outside the urban area is small and most of the missing roads are small access ways leading to fields.

5. CONCLUSION

In this paper, an automatic approach for road extraction from high resolution satellite imagery has been presented. The high-resolution images are first classified resulting into the so-called “road class image” constituting membership values for every pixel. Using these results of the classification and a number of geometric constraints, Steger lines are evaluated as road hypotheses. Our new verification process uses spectral information for the verification of road hypotheses, substantially mitigate the number of false positives, e.g., caused by small fields or hedges. Moreover, roads with high bend or changing width, e.g., affected by shadows cast on them, can be extracted without adapting the parameters. Applying the verified hypotheses, the road network is created. For the confirmation of the approach, result of the evaluation is shown, indicating the strength of the approach.
Our future strategies include the use of the spectral properties of roads together with the road width, to automatically classify roads into different road classes. From visual inspection it is possible to differentiate paved roads from dirt roads.

REFERENCES

[1] Fischler, M., Tenenbaum, J. and Wolf, H., 1981. Detection of Roads and Linear Structures in Low-Resolution Aerial Imagery using a Multisource Knowledge Integration Technique. Computer Graphics and Image Processing 15, pp. 201–223.

[2] Wiedemann, C., Heipke, C., Mayer, H. and Hinz, S., 1998. Automatic Extraction and Evaluation of Road Networks fromMOMS-2P Imagery. In: International Archives of Photogrammetry and Remote Sensing, Vol. (30) 3/1, pp. 285–291.

[3] Steger, C., Mayer, H. and Radig, B., 1997. The Role of Grouping for Road Extraction. In: Automatic Extraction of man-made Objects from Aerial and Space Images (II), Birkhauser Verlag, Basel, Switzerland, pp. 245–256.

[4] Busch, A., 1996. A Common Framework for Photogrammetry and Remote Sensing, Vol. (32) 4/1, pp. 293–298.

[5] Klang, D., 1998. Automatic Detection of Changes in Road Databases Using Satellite Imagery. In: International Archives of Photogrammetry and Remote Sensing, Vol. (32) 4/1, pp. 293–298.

[6] Wallace, S., Hatcher, M., Priestnall, G. and Morton, R., 2001. Research into a Framework for Automatic Linear Feature Identification and Extraction. In: Automatic Extraction of Man-made Objects from Aerial and Space Images (III), Balkema Publishers, Lisse, Niederlande, pp. 381–390.

[7] Stoica, R., Descombes, X. and Zerubia, J., 2004. A Gibbs Point Process for Road Extraction from Remotely Sensed Images. International Journal of Computer Vision 57(2), pp. 121–136.

[8] Dial, G., Gibson, L. and Poulsen, R., 2001. IKONOS Satellite Imagery and Its Use in Automated Road Extraction. In: Automatic Extraction of Man-Made Objects from Aerial and Space Images (III), Balkema Publishers, Lisse, The Netherlands, pp. 357–367.

[9] Amini, J., Lucas, C., Saradjian, M., Azizi, A. and Sadeghian, S., 2002. Fuzzy Logic System for Road Identification Using IKONOS Images. Photogrammetric Record 17(99), pp. 493–503.

[10] Doucette, P., Agouris, P., Stefanidis, A. and Musavi, M., 2001. Self-Organized Clustering for Road Extraction in Classified Imagery. ISPRS Journal of Photogrammetry and Remote Sensing 55, pp. 347–358.

[11] Zhang, Q. and Couloigner, I., 2004. AWavelet Approach to Road Extraction from High Spatial Resolution Remotely-Sensed Imagery. GEOMATICA 58(1), pp. 33–39.

[12] Mohammadzadeh, A., Tavakoli, A. and Zoej, M., 2004. Automatic Linear Feature Extraction of Iranian Roads from High Resolution Multi-Spectral Satellite Imagery. In: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. (35) B3, pp. 764–767.

[13] Bacher, U. and Mayer, H., 2003. Fuzzy-Classification and Ziplock Snakes for Road Extraction from IKONOS Images. In: ISPRS / EARSeL Joint Workshop on High Resolution Mapping from Space.

[14] Zadeh, L., 1989. Knowledge Representation in Fuzzy Logic. IEEE Transactions on Knowledge and Data Engineering 1(1), pp. 89–100.

[15] Wiedemann, C., 2002. Extraktion von Straennetzen aus optischen Satellitenbilddaten. Deutsche Geod- atische Kommission (C) 551, Munchen.

[16] Wiedemann, C. and Ebner, H., 2000. Automatic Completion and Evaluation of Road Networks. In: International Archives of Photogrammetry and Remote Sensing, Vol. (33) B3/2, pp. 979–986.

[17] Neuenschwander, W., Fua, P., Szekely, G. and Kubler, O., 1995. From Ziplock Snakes to VelcroTM Surfaces. In: Automatic Extraction of Man-Made Objects from Aerial and Space Images, Birkhauser Verlag, Basel, Switzerland, pp. 105–114.

[18] Heipke, C., Mayer, H. and Wiedemann, C., 1998. External Evaluation of Automatically Extracted Road Axes. Photogrammetrie - Fernerkundung – Geoinformation 2/98, pp. 81–94.