AUTOMATIC ROAD EXTRACTION FROM REMOTE SENSING IMAGERY INCORPORATING PRIOR INFORMATION AND COLOUR SEGMENTATION

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KEY WORDS: GIS, Imagery, MSI, Road Extraction, Quality

ABSTRACT:

In this paper an approach to road extraction in open landscape regions from IKONOS multispectral imagery is presented which combines a line-based approach for road extraction with area-based colour segmentation. Existing road databases are used in two ways: firstly, to estimate scene dependent parameters of the line-based approach and secondly to exclude non road regions from the extraction, also exploiting the colour information. The images and reference data for the evaluation are identical to the information used in a recently conducted EuroSDR test on automatic road extraction. Therefore, the results can easily be compared with the published ones. It is shown that our new approach with reduced human interaction for the parameter optimisation obtains results similar to the best ones of the EuroSDR test.

1. INTRODUCTION

The road network is an important component of the infrastructure in every country. Therefore, up-to-date and accurate information on the road network is of vital importance. Today, short up-date-cycles and high quality digital road databases are requested. One means to satisfy these demands is to make use of digital remote sensing imagery for automated road network extraction, quality control and update.

Recently, a test on automatic road extraction algorithms has been carried out by EuroSDR (Mayer et al., 2006). The results show that automatic road extraction approaches for open landscape based on aerial images or high resolution satellite imagery are operational, although lacking quality and efficiency in some instances. Two issues were identified which contribute to enhanced results: the use of 1) colour information and 2) prior information for the extraction of roads. Although the latter aspect could not be verified by the test, because no prior information was offered, the authors of the EuroSDR test report made this general statement based on their experience and feedback from the participants. We can confirm this statement, because in own experiments the incorporation of existing road databases into the road extraction lead to better results compared to an approach where this data was not incorporated (Gerke et al., 2004).

In our current research presented in this paper we use pan-sharpened multispectral IKONOS imagery to delineate road centrelines in open and rural landscape areas. Prior information, derived from an existing road database, is used in two ways: firstly, to estimate scene dependent parameters of a line-based road extraction approach and secondly to exclude non-road regions from the extraction, also exploiting the available colour information.

The background of our research is given by the WiPKA-QS-Project, where the German authoritative topographic reference data set ATKIS-DLMBasis and the MGCP (Multinational Geospatial Coproduction Program) dataset being produced by the German Federal Armed Forces (Grelck and Müller-Grunau, 2005) are to be automatically verified using remote sensing imagery (Busch et al., 2004).

Results of our approach document that both aspects, namely the exploitation of available prior information and the use of colour for road extraction significantly enhance the overall performance, i.e. the correctness and completeness of the automatic road extraction.

2. RELATED WORK

In this section, a brief overview of existing road extraction approaches for open and rural landscape areas is given. The overview is not meant to be complete; it focuses on some aspects which are related to our present work and the approaches only represent a small part of the whole range of papers available. More complete overviews on road extraction approaches are presented e.g. in (Hinz and Baumgartner, 2003), (Hinz, 2004) and (Gerke, 2006). We first concentrate on the geometric road model which is used for the extraction, i.e.: line vs. area-based road extraction. The role of colour information is also discussed in this context. Secondly, the way other authors incorporate existing prior information is presented.

2.1 Line-based vs. area-based road extraction and use of colour information

In (Wiedemann, 2002, 2003) roads are modelled as linear objects in aerial or satellite imagery with a resolution of about 1 to 2m. The underlying line extractor is the one introduced in (Steger, 1998). The initially extracted lines are evaluated by fuzzy values according to attributes, such as length, straightness, constancy in width and in grey value. The final step is the grouping of the individual lines in order to derive topologically connected and geometrically optimal paths between seed points Seed points are end points of lines which reached a cost minimum in the evaluation score. The decision whether extracted and evaluated lines are grouped into one road object is taken based on a collinearity criterion, allowing for a maximum gap length and a maximum direction difference.

One main problem with the line-based approach is the tuning of parameters for line extraction. The parameters depend on the object and on context. For instance, a dark asphalt road in a desert environment can be delineated more reliably and accurately than a vegetated path between a cultivated environment, e.g. between two grassland fields. Moreover, the contrast conditions depend on the actual illumination conditions of the satellite scene. To compensate these variabilities of road extraction results, Hinz and Wiedemann (2004) described an extended approach that checks the final results by internal evaluation measures. This enables a prediction about the adaptation level of the used parameter set and may lead to alternative settings.

In (Zhang and Couloigner, 2006) an area-segmentation-based approach is developed. Firstly, the multispectral image is segmented using the unsupervised K-means clustering method. Road segments are filtered by evaluating the resulting segments based on shape descriptors. Finally, the road centrelines are retrieved from the grouped road segments using a skeletonisation method.

Also in (Mena and Malpica, 2005) colour information is used for the segmentation of the image. Mainly, the evidence delivered by three different statistical approaches is combined and leads to an enhanced segmentation of the imagery. The first source of evidence is given by a supervised classification, employing the Mahalonobis distance. The second source is obtained from the comparison of the colour distribution in the neighbourhood of individual pixels with the trained distributions. For this purpose, the Bhattacharyya distance is used. The last source of evidence is given by Haralick features derived from the co-occurrence matrix. The segments obtained after evidence fusion are then skeletonised to obtain the road centre axis.

In (Bacher and Mayer, 2005) and (Bacher, 2006), a combined approach is introduced. A pixel-based multispectral classification is used to generate a so-called roadclass-image. The training information for the supervised classification is obtained from a very strict initial road extraction according to Wiedemann (2002, 2003), and using additional parallel edge information (Baumgartner et al., 1999). The subsequent road extraction is then conducted according to Wiedemann (2002, 2003), but the roadclass-image is used to additionally evaluate the extracted lines.

One problem with the presented approaches based on area segmentation is that the estimation of the road centreline is only based on classified segments. Consequently, the accuracy of the resulting centreline is decreased (Mayer et al., 2006). In (Zhang und Couloigner, 2006) shape parameters are applied to filter road segments, i.e. to eliminate parking lots, buildings etc. from the segments. However, no image information is used at this stage, leading to misclassification of segments in some cases.
Bacher (2005, 2006) uses a line-based approach, but also exploits colour information for an enhanced classification of extracted lines. However, the sensitive parameter setting for line extraction is not further automated in this approach.

2.2 Incorporation of prior information

In (Doucette et al., 1999) the information from a coarse resolution road database is used to initialise road extraction based on a Neural Network approach, i.e. the database information is used to provide input samples. In (Bordes et al., 1997) and (Zhang and Baltsavias, 2002; Zhang 2004) road databases are used to specify the type of road and attributes such as the width. This information is employed to define hypotheses for the appearance of roads. Features extracted by means of image analysis are then used to evaluate these hypotheses.

One interesting result of these approaches is that although the representation of the database objects is very coarse, it is good enough for limiting the search space and making assumptions on the appearance of the objects due to the type given in the database.

The approach presented in (Mena and Malpica, 2005) also makes use of prior information as explained above. It is used to define the feature space for colour segmentation.

3. THE NEW APPROACH

From the brief overview of the related work, some lessons can be learned. If applicable, the line-model should be used. This is the case when the background objects are homogeneous. However, the problem of line extraction approaches is the tuning of parameter which is object and scene dependent. Furthermore, existing research shows that colour information is an adequate means to distinguish road objects and background.

This paper presents a new approach to road extraction in open landscape using IKONOS imagery. The approach has the following properties:

- It makes use of the line-model and extraction algorithm as proposed by Wiedemann (2002, 2003)
- GIS database objects are used as prior information
- Radiometric properties of the roads, in this case the contrast between road surface and background are trained for every individual scene using the prior information from the road database
- Colour information is used to segment background objects and exclude them from the extraction.

3.1 Training of radiometric parameters

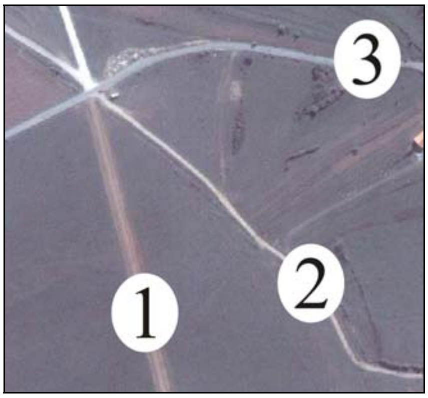


Figure 1: IKONOS sub-image with three different roads

Figure 1 shows an example of rural road objects with different surfaces. The surface appearance is correlated with the given road classes. Roads for traffic are mainly sealed and mostly consist of concrete or asphalt. In contrast, agriculturally paths often consist only of gravel or sand and are partly covered by vegetation. Additionally, the variety of possible local backgrounds, i.e. cropland, grassland and wood, leads to a number of possible radiometric combinations for roads and their local background. Our assumption is that given a representative set of prior information on road objects in a particular (satellite) scene, the most critical parameters for line-based road extraction can be estimated automatically. The prior information is obtained from GIS road data. Appropriate information includes geometry, width, classification and the image co-registration of all given road objects.

The core of the parameter training algorithm is realized by a radiometric histogram analysis of road regions in high resolution one-channel imagery. In our application we use panchromatic imagery as well as the NDVI channel which was computed from the pan-sharpened MS channels. For each road object, which is registered in the GIS database, a specific image region is generated, based on the given road centre axis and the attribute *road width*. If no road width is available, a default value is used. The resulting region width is reduced to exclude most of the mixed pixels at the road border. Consequently, it is assumed that the majority of the region pixels belong to a road. Additionally, for each object a second and a third region (one to the left, the other to the right of the road region) are generated to refine radiometric information about the local background. Once again mixed pixels are excluded by a defined minimum distance from the analysed object. Figure 2 shows an example for a generated road region (blue) and the two regions which represent the roads local background (yellow).

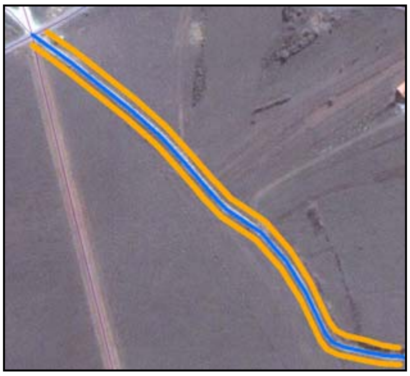


Figure 2: Buffer of road object (blue) and local background (yellow)

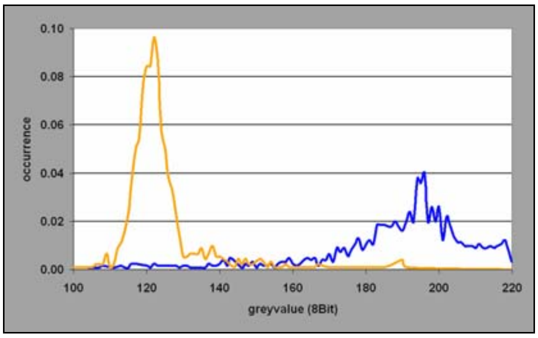


Figure 3: Histogram of a bright dirt road (blue) and its local background (yellow)

Figure 3 shows the histogram of the bright dirt road with homogeneous local background. In contrast, Figure 4 shows a homogeneous dark asphalt road with a typical heterogeneously local background. From the histograms this evident, that the parameters for the line extraction should be selected according to the road class. Thus, if information on road classes is available, the procedure described in the following is applied per road class.

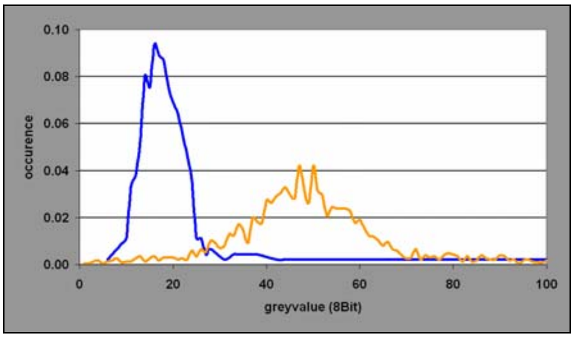


Figure 4: Histogram of a dark asphalt road (blue) and its local background (yellow)

Based on the calculated object specific histograms the following radiometric parameters are derived:

- *Homogeneity* along the line object assumed to be a road. The line extraction operator requires pixels with similar greyvalues along the road centreline to form a line object.
  We calculate the homogeneity as the standard deviation of greyvalues from the road histogram.
- *Contrast* between road and local background. The line extractor requires a minimum difference of pixel-greyvalues across the road to form a line object.
  Local background can consist of different objects. We look for the contrast between the road and the most similar background object, thus the smallest difference between the peak of the road pixels and a peak of the background pixels is required. The peak of the road pixels is computed as follows: first we only consider greyvalues which account for the top 80% occurrence in the histogram in order to eliminate possible disturbances. We use rank filtering to obtain this result. We then compute the median of the remaining road pixels as the desired peak value. In order to detect the background peak we apply the same rank filtering. Starting from the road peak we then find the closest local maximum. The difference between both peaks is the contrast.
  The contrast is used to decide weather the investigated road is brighter or darker than the background. The differentiation between dark and bright roads is used to classify the radiometric parameters into two categories. The line extractor separates between dark and bright line models. Accordingly, a dark–bright specific parameter derivation is useful.
- *Global threshold* is defined as the higher (dark roads) or the lower (bright roads) limit to generate a region of interest containing the roads.
  The threshold is extracted as the maximum value (dark roads) or the lowest value (bright roads) from the rank filtered road region histogram.

In terms of the line extraction algorithm, only plausible results are considered for further calculations. Therefore, the refined *Homogeneity* has to be smaller than the resulting *Contrast*.

Consequently, the three parameters are calculated per given GIS road object. The next task is to find the optimal values for a scene and – if available – a road class dependent road extraction. For this task, three sorted lists are created, one for every parameter where the individual values are listed. Geometric or attribute errors of the GIS database have to be considered in the parameter training algorithm. It is assumed that the parameters derived from wrong GIS road objects with plausible results only influences some of the top values of the sorted lists, therefore rank filtering is applied to derive the radiometric parameters. Other recent work like (Bacher 2005, 2006) uses this method with a similar aim.
The details of rank filtering depend on the overall GIS database quality. Empirical investigations showed that a rank of 10 % seems to be applicable. To guarantee the robustness of the system towards area wide incorrectness of GIS data a minimum number of training objects has to deliver plausible parameter values. Otherwise standard parameter settings are automatically used for the extraction algorithm.

3.2 Colour segmentation

The available IKONOS imagery contains four spectral bands: red, green, blue and infrared with a ground resolution of approximately 4m, but is pan-sharpened to a nominal resolution of 1m. The used line extraction approach of Wiedemann (2002, 2003) does not consider multispectral information directly. Therefore, advantageous channel combinations like NDVI or intensity are still used in the extraction step. A separated line extraction conducted in every available IKONOS channel is not applied. According to our experience the different colour bands provide no significant additional information. Nevertheless, this information is more valuable in an area-based approach. Therefore, a colour segmentation step is added, to enhance multispectral application. Thereby, a region of interest (ROI) is defined for the further road extraction step. The basic ambition is to determine the range of spectral signatures which together contain all possible spectral combinations of roads in a specific scene. The overall calculation is based on RGB colour space with 8 bit per channel. Although, the NIR channel would probably contribute valuable information, we make no use of this channel up to now. The usage of an alternative colour space, like HIS or HSV, offers to our experience no significant advantage for segmentation.

3.2.1 General approach

Similar to the parameter training approach, explained in the preceding section, roads from the given GIS database are used to define the training region. If available, the attribute *road width* is used to generate a region that contains all road objects. This training region is further classified using the attribute *road class*, if available, to enhance the spectral analysis. In contrast to the parameter training approach an object specific procedure is not applied. All pixels from the training region are transferred to RGB colour space. In this step, the number of occurrences of every spectral combination is registered. Based on these values, a histogram analysis is applied as described below, to build up different clusters in feature space. Next, all image pixels within ROIs are classified into road and non-road pixels.
Noise effects of the resulting image regions are reduced by erosion and the adjacent regions are connected. Moreover, simple shape descriptors are used to identify image regions which are not consistent with the road model, i.e. large crop fields. These large regions are sometimes spectrally similar to roads and are eliminated. Subsequently, based on the topological characteristics of the road network, all isolated region parts are also eliminated. The resulting ROI is extended along the borders to include the local background for the line-based road extraction in the image.

3.2.2 Histogram analysis

The definition of relevant clusters in feature space is difficult. Because of the limited road width, the pixels belonging to road objects are often heavily influenced by the spectral properties of the local background. Only for wider asphalt roads a clear differentiation from the background can be achieved from the training data. These roads are often characterised by a significant saturation in the blue band. Additionally, a lot of its pixels are influenced by low saturation objects like bright road markings or dark wheel tracks. In contrast, smaller dirt roads have no predictable spectral signature. Because of the described difficulties, the colour segmentation algorithm is currently reduced to a histogram analysis of the RGB-feature space including rank filtering.
Again, it is assumed that the GIS database used for the training is mainly correct. Consequently, the spectral signature of roads is supposed to occur frequently. A histogram analysis based on the RGB colour space is carried out in a similar manner just as described for the parameter training. The computed number of occurrences of every spectral combination gives evidence about the membership of scene specific road classes. Consequently, all occurring spectral combinations are sorted according to their frequency. Based on the sorted list, a heuristic threshold for rank filtering is used for the classification. This threshold depends mainly on the overall quality of the used GIS database. For the tested GIS database, an empirical determination has shown that the colour information from the top 80% of all analysed pixels represents the scene depended road surfaces.

4. RESULTS

In order to be able to compare our approach with the recently published results from the EuroSDR test on road extraction (Mayer et al. 2006), we use the same pan-sharpened IKONOS imagery and reference data for the evaluation. They depict some different scenes in the Kosovo. Our test is restricted to the rural hilly scenes of the EuroSDR test, shown in Figure 6a and 6b. The urban IKONOS scene is excluded from the following results because the overall approach is designed for open landscape.
GIS road data is necessary prior information for our method. To evaluate the impact originating from different input data quality, we created three different GIS road datasets per IKONOS image:

- SET_A: a “realistic” dataset: most of the digitised roads are correct and show a good positional accuracy, but some roads which are visible in the imagery are missing in the dataset, and some objects from the road database are not correct at all, i.e. they do not exist in the imagery. To simulate a realistic dataset, errors were manually introduced into the EuroSDR reference dataset (Figure 5-dotted red lines).
- SET_B: the EuroSDR reference dataset which is correct in every aspect (Figure 5-yellow lines)
- SET_C: a totally incorrect road data set.

Set_A reasonably simulates situations where a road database exists and is used for the training. Set_B is chosen to have an idea how well the correct dataset can be extracted if the same data is used for the training. Set_C is chosen to be able to conduct a sensitivity analysis, i.e. to test the approach with useless prior information. Since both images have the same size, we simply chose as Set_C for a particular scene the Set_B of the other scene. The following results were obtained with geometric information from the different datasets. The attributes road width (cf. 3.1) and road class were not available in the EuroSDR reference dataset. Therefore, constant default values are used.

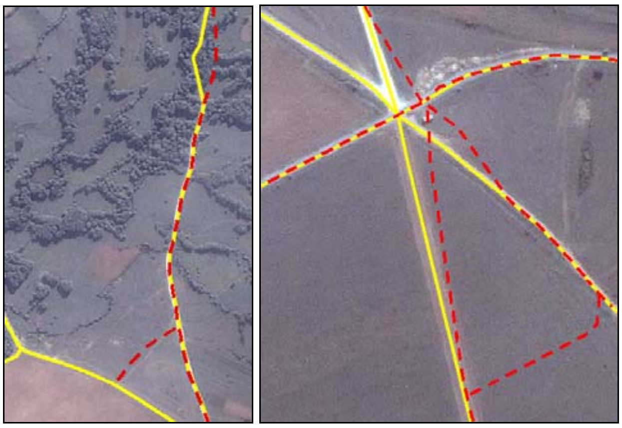


Figure 5: SET_A: realistic dataset (dotted red) and SET_B: reference dataset (yellow), exemplary zooms for tested imagery

The evaluation of the results is done applying the same reference data as used for the EuroSDR test. Additionally, the measures *completeness, correctness* and *RMS* are calculated using the same software as in the test, therefore the results can easily be compared. Firstly, only the results of radiometric parameter training are presented. Afterwards the results of the additional application of the colour segmentation step are shown.

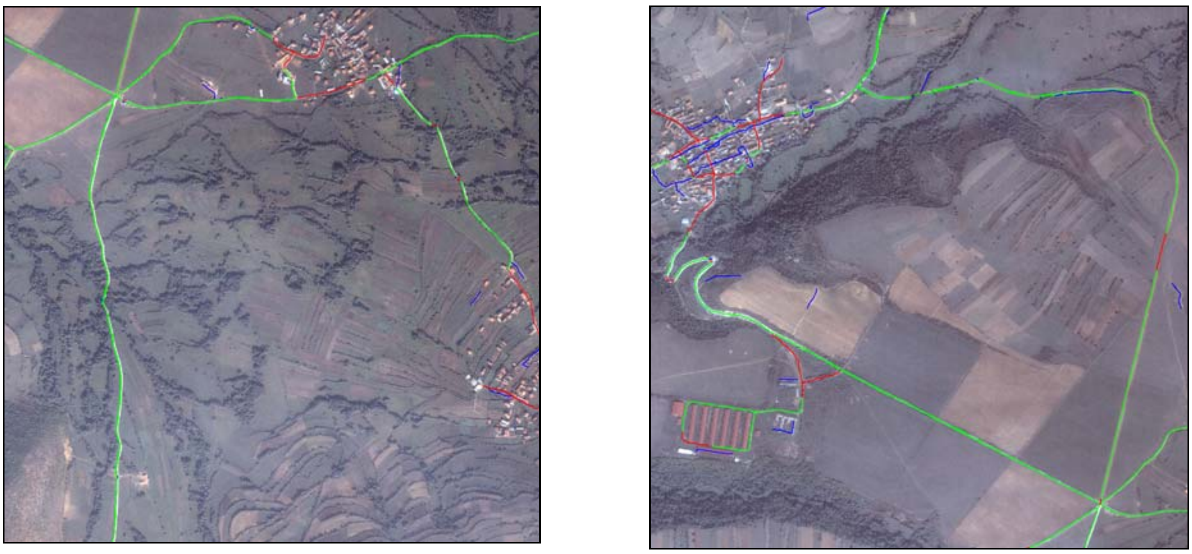
4.1 Training of radiometric parameters

The algorithm for parameter training and line extraction is separately applied to the NDVI and the intensity channel. Both channels provide complementary information for road extraction, as already shown in other research work. After line extraction, the results are fused and evaluated as a combined result. For Set_A we provide results using only the intensity channel and including also the NDVI channel. To guarantee the focus on radiometric parameters, the geometric parameters (for details see Wiedemann, 2002) are held constant for all used datasets and images.

No	Name	Completeness	Correctness	RMS [pix]
	IKONOS_3_Sub2			
1	Best_EuroSDR	0.85	0.91	1.59
2	Gerke_EuroSDR	0.75	0.52	1.35
3	SET_A_(noNDVI)	0.78	0.91	1.22
4	SET_A	0.83	0.90	1.22
5	SET_B	0.83	0.92	1.22
6	SET_C	(0.75)	(0.52)	(1.35)
	IKONOS_3_Sub1			
7	Best_EuroSDR	0.81	0.87	0.97
8	Gerke_EuroSDR	0.80	0.65	1.53
9	SET_A_(noNDVI)	0.75	0.75	1.20
8	SET_A	0.77	0.76	1.42
9	SET_B	0.76	0.75	1.40
10	SET_C	(0.80)	(0.65)	(1.53)

Table 1: Evaluation Results. Grey rows are from (Mayer et al. 2006)

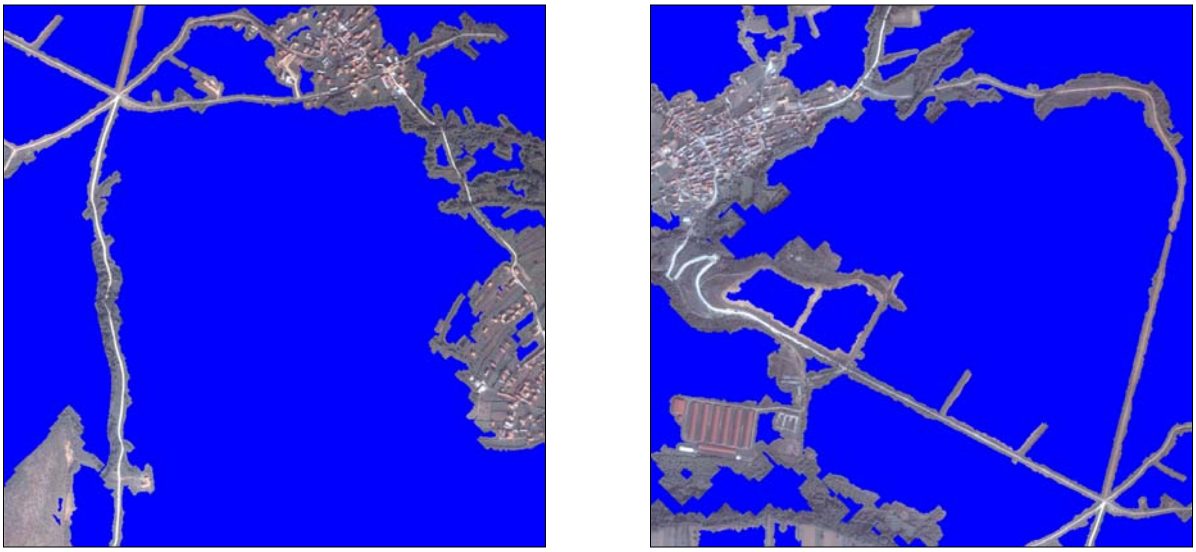
Table 1 contains the best result from the EuroSDR test together with those obtained in our investigations. Generally, the extraction results, focused on open landscape areas, are nearly complete and correct, shown in Figure 6a and Figure 6b.
Compared with Best_Euro_SDR (Karin Hedman) of IKONOS_3_Sub2 our RMS is smaller. The Best_Euro_SDR (Uwe Bacher) of IKONOS_3_Sub1 summarises a very good RMS and high completeness and correctness. This advantage compared to our approach is mainly caused by an enhanced extraction in the built-up area.
The use of NDVI is not necessarily advantageous because many roads are dirt roads, which are covered by vegetation.



(a) IKONOS_3_Sub2

(b) IKONOS_3_Sub1

Figure 6: EuroSDR test images, SET_A-extraction results: Correctly extracted roads are given in green, incorrectly extracted roads in blue and missing roads in red.



(a) IKONOS_3_Sub2 (b) IKONOS_3_Sub1

Figure 7: ROIs, trained with SET_A

The small differences between the results from SET_A and SET_B show that the rank filter works efficiently. Therefore, realistic imperfect databases can be used for our problem. The parameter training algorithm has also registered the completely incorrect datasets (SET_C) and did not result in plausible parameters. Thus, useless prior information is detected automatically in our approach. In order to still extract roads the human operator has to manually select appropriate parameters. In this case, the results correspond with Gerke_EuroSDR, because in both tests the same parameters set where selected.

Compared with Gerke_EuroSDR in particular the correctness of the recent tests is enhanced. The main reason for this is the tuning of the global threshold parameter.

4.2 Colour segmentation

The ROI results for the line extraction algorithm based on colour segmentation are shown in Figure 7. Large areas with multispectral signature of trained roads are found within settlement areas. Therefore, urban areas are shown as compact ROIs. The generated regions contain nearly all road objects including local background - only the large background areas are excluded from line extraction.

No	Name	Completeness	Correctness	RMS [pix]
	IKONOS_3_Sub2			
4	SET_A	0.82 (-0.01)	0.90 (±0.00)	1.22
5	SET_B	0.82	0.91	1.22
	IKONOS_3_Sub1			
8	SET_A	0.77	0.79 (+0.03)	1.42
9	SET_B	0.76	0.78	1.40

Table 2: Evaluation results. Numerical values in brackets describe differences towards prior results.

The colour segmentation algorithm is used as a separate module for the whole road extraction process. Therefore, the overall result can be compared to the results presented in Table 1. The evaluation (Table 2) shows no significant enhancement. Only for IKONOS_3_Sub1, the correctness is slightly increased, because some incorrect line objects are excluded. However, in the IKONOS_3_Sub2 image a correct object is missing, because its multispectral combination was not sufficiently represented in the training dataset, resulting in a marginally smaller completeness value.

Because of the mainly bright roads and the dark background, the usage of the trained global threshold as shown with the former test and the calculation of ROI from colour segmentation achieve similar results. Thus, in this case the additional colour information does not seem to be necessary for road extraction.

As before the usage of realistic (SET_A) and perfect reference dataset (SET_B) achieves similar results.

5. CONCLUSIONS AND OUTLOOK

In this paper, we present two methods to incorporate prior information into a line-based road extraction algorithm. The first method aims at parameter estimation for the line extraction. The parameters being automatically tuned are the contrast between road and background, the homogeneity within the road objects and a global threshold for masking out non-road areas. The method turns out to be robust against errors in the available prior information and it was shown that the obtained results are better than results which have been achieved with the same road extraction algorithm and manually tuned parameters.

Multispectral colour information is not directly used within our basic method – the road extraction is applied to intensity or NDVI channel. The second refinement introduced here makes explicit use of the available colour information. Non-road areas are identified based on a statistical analysis of the RGB colour space and the available prior information on road data. The results obtained with this second method in combination with the first method do not significantly differ from the results where only parameter tuning was applied. This observation can be traced back to the fact that the background in the given images is relatively homogeneous and therefore the estimation of the global threshold as done with the first method nearly masks out the same region as the multispectral approach. Additional tests will further investigate this issue.

In the EuroSDR test to which we refer it was stated that the current automatic approaches available in the literature and implemented in some prototypes have gained already practical relevance, at least for open landscape regions. From a practical point of view, the refinements presented in this paper should contribute to an even better acceptance of a road extraction system, because the tiresome tuning of parameters is significantly reduced. A prerequisite, however, is that the database with the prior information contains all kinds and classes of desired roads.

The parameter tuning can be further enhanced, in particular regarding the geometric parameters for road extraction. For instance, to extract winding roads we needs, other parameters compared to the extraction of straight highways. The prior information from the GIS database can be used to determine the types of roads contained in the current scene and consequently the respective parameters can be optimised.

The colour segmentation method needs also to be enhanced in several regards. Three issues are in the focus of our ongoing work. In our method we do not use the infrared channel yet. In regions where the background of a road object is densely vegetated and the road surface itself is sealed, the incorporation of the infrared information is supposed to contribute valuable additional information; this was also shown by other participants of the EuroSDR test. Additionally, the radiometric information content of the used 8 bit image is significantly reduced compared to the original 11 bit images. In future we will make use of the complete radiometric information. Finally, we are currently investigating means for alternative clustering in RGB-(IR)-(frequency)-feature space.

The presented method is being used in a system for the assessment and updating of existing GIS databases (Busch et al., 2004, Gerke, 2006). It is expected that the use of both methods introduced in this paper will contribute to an increased efficiency and reliability of the developed system.

ACKNOWLEDGEMENTS

The test and reference data was made available by Helmut Mayer and Uwe Bacher. The work is funded by the Bundeswehr Geoinformation Office (AGeoBw), Euskirchen, Germany. We gratefully acknowledge this support. We would also like to thank the anonymous reviewer for their valuable comments.

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