DISCRIMINATION BETWEEN URBAN AREA AND VEGETATION IN HIGH-RESOLUTION IMAGES USING MARKOV RANDOM FIELDS (MRF)

Lippok, A.[1] and Reulke, R.[1]

1. Humboldt-Universität zu Berlin, Institut für Informatik, Computer Vision, Unter den Linden 6, 10099 Berlin, Tel.: +49 30 2093 3044, Fax: +49 30 2093 3045, (lippok,reulke)@informatik.hu-berlin.de

ABSTRACT

The automatic extraction of traffic data from digital images is a challenging task and implies an extensive pre-processing of this data. An important information which simplifies the further extraction of traffic objects is the recognition of active traffic regions. A possible approach is masking of streets using platform attitude and position together with a digital street map (i). But often such digital maps are not available or at least inaccurate (ii).To improve differentiation between streets and environment, image based methods can be used. The aim of this work is the detection of active traffic regions (e.g. discrimination of urban area and vegetation) in high-resolution aerial photographs with image processing methods.

The segmentation of images was realised on the basis of texture features. There are various texture features which are suggested for segmentation in published literature. But unfortunately most of these approaches are barely applicable for the segmentation of real digital photos. In this paper Markov Random Fields (MRF) for feature determination are used, because MRFs enable the modelling of texture specific interactions between pixels.

From the different existing MRF models the autobinomial model was chosen, which is known in image processing since the 80ies (iii). For obtaining reliable results the parameterization of the MRFs with synthesised images was investigated. Afterwards different model parameters, that influence the segmentation, were studied using standardised Brodatz textures (iv). Thus the capabilities and limits of this method can be characterised.

It was possible to segment precisely the collages of Brodatz textures with MRFs. However, the quality of segmentation depends significantly on some additional factors that have to be considered, e.g. noise and image normalisation. Concerning these parameters the realised segmentation of aerial photos is likewise good. Nevertheless, the segmentation suffers from radiometric poor photographs. Moreover heterogeneous areas, e.g. urban areas with lot of single trees, make segmentation incorrect.

MRF MODELING

If the probability distribution of the grey level for each pixel z_i only depends on the grey levels of the neighbouring pixels, the image is called Markovian. Such images can be described by a Gibbs fields. For this approach the image is characterised by the conditional probability. This probability distribution denotes the probability for accepting a grey level g_i by a pixel z_i, assuming the neighbouring pixels Z^i have the grey levels g^i (v).

$$P(z_i = g_i \mid Z^i = g^i) = \frac{1}{S} e^{-H(g_i, g^i)} \quad \text{with} \quad S = \sum_{g=0}^{G} e^{-H(g, g^i)}$$

S is called partition sum, whereas H stands for the energy function characterizing the Markov random field. In most cases this energy function is parameterised by a vector $\theta = [b_0, b_{1,\dots}]^T$. This parameter vector is used for segmentation as a multidimensional texture feature. The used autobinomial model has the following energy function (vi):

$$H_\theta(g) = H_\theta(g_i, g^i) = -\ln\binom{G}{g_i} - g_i \cdot \eta \qquad \text{with} \qquad \eta = b_0 + \sum_j b_j \frac{g_j + g_j^{'}}{G}$$

In the first term each grey value g_i is weighted separately. Because of the special structure of the autobinomial coefficients the middle grey values are stronger weighted than the bright or dark pixels. In the second term the grey value g_i is applied against his neighbouring pixels. In doing so different neighbourhood systems can be used (see figure 1). As this weighting is calculated with the vector θ, the parameter vector specifies the MRF.

	x_{12}	
x_{11}	x_i	x'_{11}
	x'_{12}	

x_{22}	x_{12}	x'_{21}
x_{11}	x_i	x'_{11}
x_{21}	x'_{12}	x'_{22}

	x_{44}	x_{32}	x'_{41}	
x_{43}	x_{22}	x_{12}	x'_{21}	x'_{42}
x_{31}	x_{11}	x_i	x'_{11}	x'_{31}
x_{42}	x_{21}	x'_{12}	x'_{22}	x'_{43}
	x_{41}	x'_{32}	x'_{44}	

Figure 1: Often used neighbouring systems (vii,viii) with 3 (left), 5 and 11 (right) parameters.

Before segmenting a given image, the parameter vector θ has to be determined. For this purpose two different methods were used. The first method determines the parameter with the maximum pseudo likelihood (MPL) estimation. This approach maximises the overall probability for the image. Unfortunately the overall probability for the autobinomial model is unknown. Therefore Besag's suggestion (ix) was used, which approximates the overall probability by the product of all conditional probabilities:

$$\theta_{MPL} = \arg\max_\theta P_\theta(g) \ \text{ with the approximation } \ P_\theta(g) \approx \prod_{i \in \Re} P_\theta(g_i \mid g^i)$$

A consequence of the complexity of this probability distribution function is, that different local maxima may exist. The simulated annealing method was used to avoid local maxima and find the global maximum.

As a second method the conditional least square (CLS) estimation for parameter determination was used (vi). This approach attempts to minimise the error between the given picture and an expected image. By means of the least square adjustment calculus the parameter vector θ can be calculated as follow.

$$\theta_{CLS} = \arg\min_\theta \sum_i (g_i - \tilde{g}_i)^2 \qquad \hat{\theta} = (G^T G)^{-1} G^T d$$

Whereas $\tilde{g}_i$ are the expected grey values, G is a matrix containing grey values of the neighbouring pixels and d is a logarithmic vector of this grey values. Both methods deliver about the same results. The calculus of CLS however is significantly faster and was used for further calculations.

The investigation of MRFs for texture segmentation was done in several steps. First the validity of the parameter extraction was analysed to figure out, whether the parameter extraction is reproducible, and to find the circumstances under those the algorithm is stable. In order to compare the extracted with the correct parameters synthesised MRF images were used. From a given parameter vector (therewith from a given MRF) the images were synthesised with a Markov chain and the Gibbs sampler. This iterative procedure is e.g. explained in (v). Typical parameter sets were extracted from Brodatz textures

The effects of noise, image scaling, neighbourhood system size and of a normalisation of the parameters were also examined.

In order to achieve a quasi-continuous scaling and avoid aliasing effect, the bicubic resampling method was applied. Examination of the fourier spectrum of the scaled pictures has shown that low-frequency information is preserved by this method.

After investigating the parameter extraction the segmentation of Brodatz textures was researched. Using Brodatz textures various influencing like the sunset were avoid. The segmentation was realised with the point based method of support vector machines. This segmentation system is suitable, as it facilitates fast segmentation in a multidimensional feature space.

The effects on segmentation of a radiometric image normalisation, the parameter normalisation, the texture window size, the neighbourhood system size as well as of an image scaling were analysed. For quantifying the influence of scaling under different conditions, all segmentations were made in the quasi-continuous scaling room and the results diagrammed with a logarithmic abscissa.

Considering the achieved results high-resolution aerial photographs were segmented. Images of a DALSA camera (made available by DLR) and DMC pictures (made available by Intergraph) were used.

RESULTS AND DISCUSSION

All analyses are made with many different images or image collages. Some examples are shown below.

Validation of the Parameter Extraction

The extraction of the parameter vector from the synthesised images doesn’t always work perfectly. Although the extracted parameter vector has the right orientation it has the wrong length. To ensure reproducibility of the extraction, the parameter vector has to be normalised to a unit length.

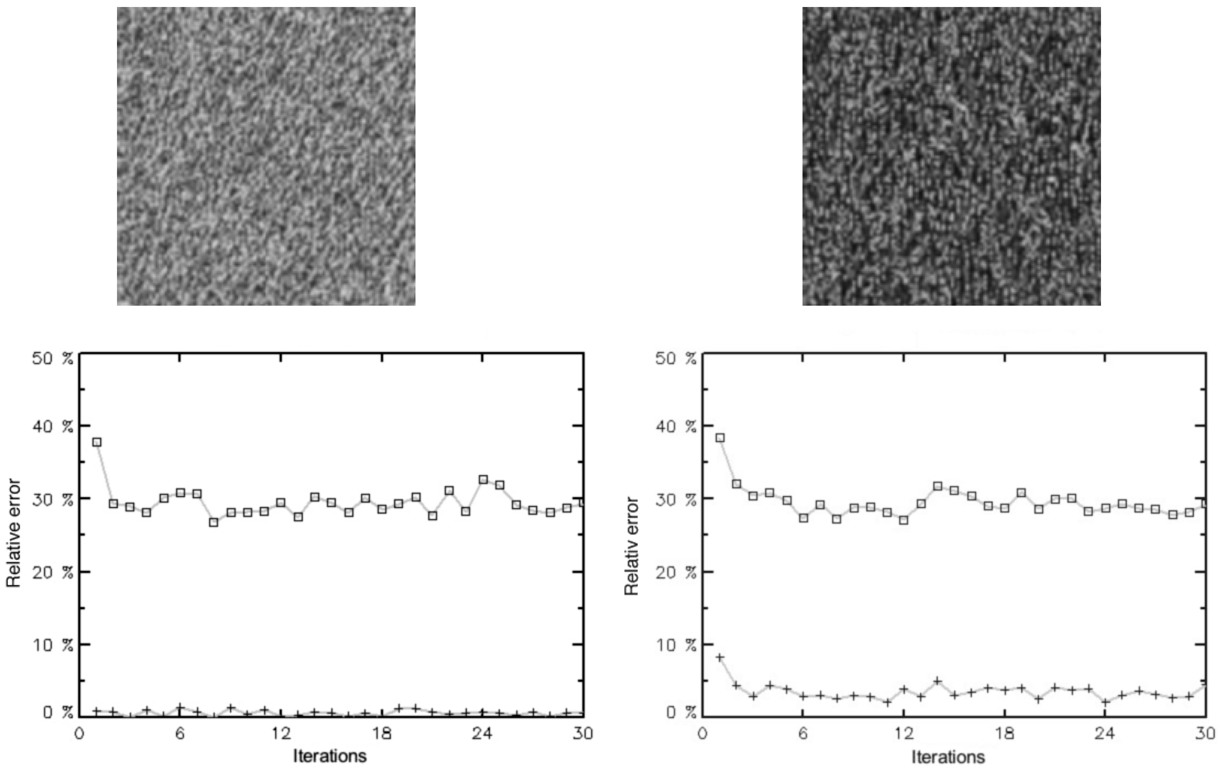

Figure 2: Error of the parameter extraction with not normalised (□) and normalised parameters (+) and the corresponding synthesised textures.

Using the normalised parameters, the extraction can be done with relatively small errors.

The parameter extraction is very sensitive to sensor noise. Already at a noise level of 5% there is an obvious degradation. Even in this case a normalisation of the parameter vector has a positive effect.

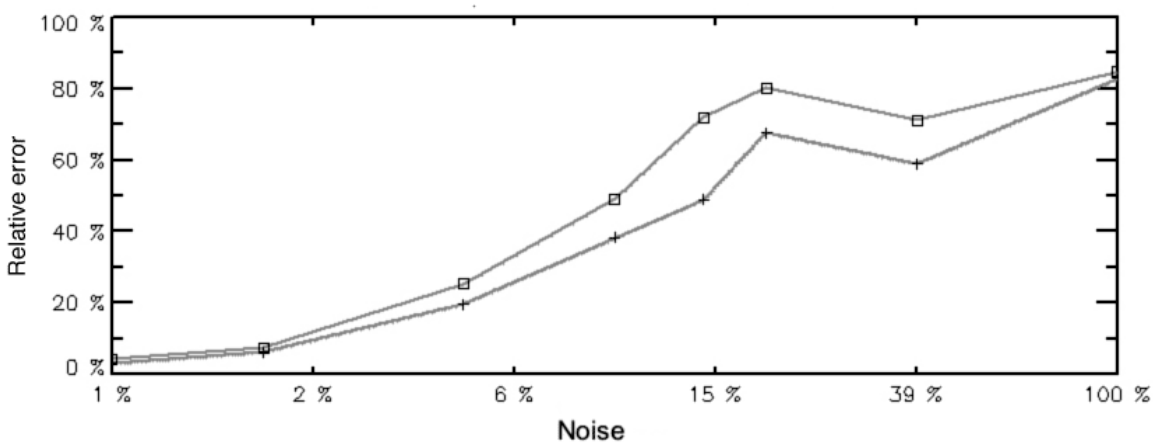

Figure 3: Error of image segmentations with different degrees of noise with (+) and without (□) parameter normalisation.

The extension of the neighbourhood system has barely influence on the parameter extraction. With enlarged neighbourhood systems only new parameters are added. In enlarged NBSs the existing parameters represent the same pixel interaction.

In contrast to that the scaling of the picture has a strong influence on the model parameters.

Examining the influences on segmentation

A radiometric normalisation of the image is useful. The segmentation is not always improved, but shading effects can be avoid effectively. The normalisation to a uniform mean and deviation leads to better results than a histogram equalization.

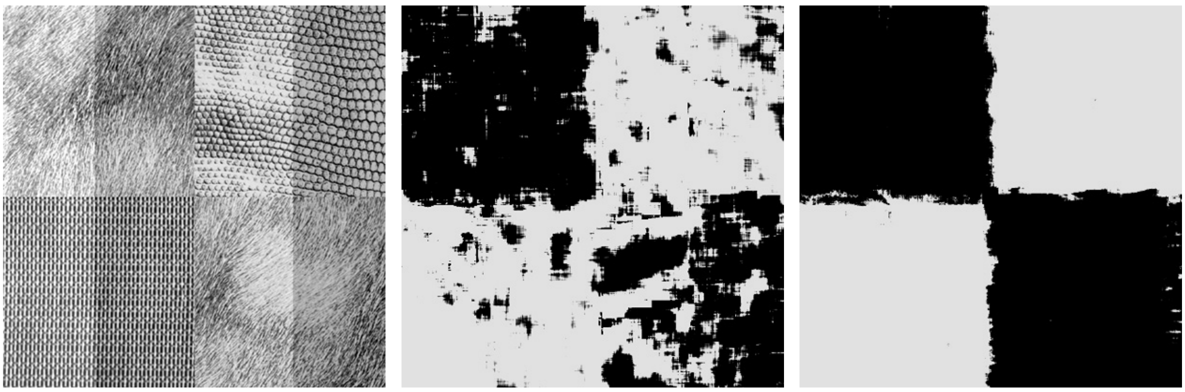

Figure 4: Segmentation result with shading effects: without normalisation (error = 16%) (middle), with normalisation (error = 2%) (right)

The normalisation of the extracted parameter vector also yields better segmentation results. It was already shown that the parameter normalisation is necessary for a valid parameter extraction. Accordingly this has a positive impact on the segmentation as well.

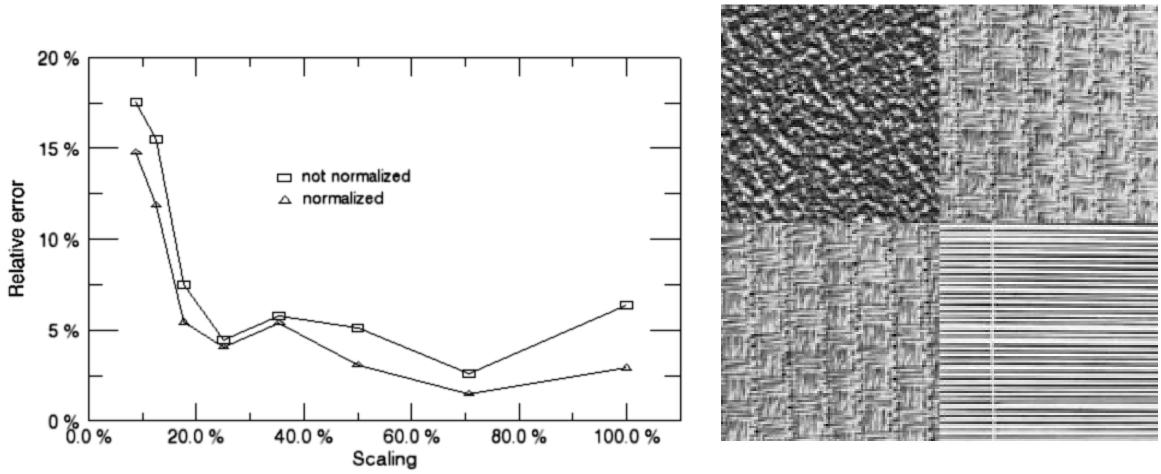

Figure 5: Example for segmentation errors with and without parameter normalisation

The texture window size and the scaling strongly affect the segmentation. However for each picture different values lead to an optimal result. In general the following trend can be derived:

The more finely the texture, the smaller the texture window and the higher the scaling that should be chosen. However, no generally applicable rules can be drawn from these results. The texture window size and the scaling must be adjusted for every special texture.

By contrast the neighbourhood system has only a little influence on the segmentation results. The reason is that only a few parameters contribute to the description of the texture quality. Additional parameter (so a bigger neighbourhood system) do not contain other information and do not enhance segmentation results. Usually a NBS with 10 neighbours is adequate and was used for further investigations.

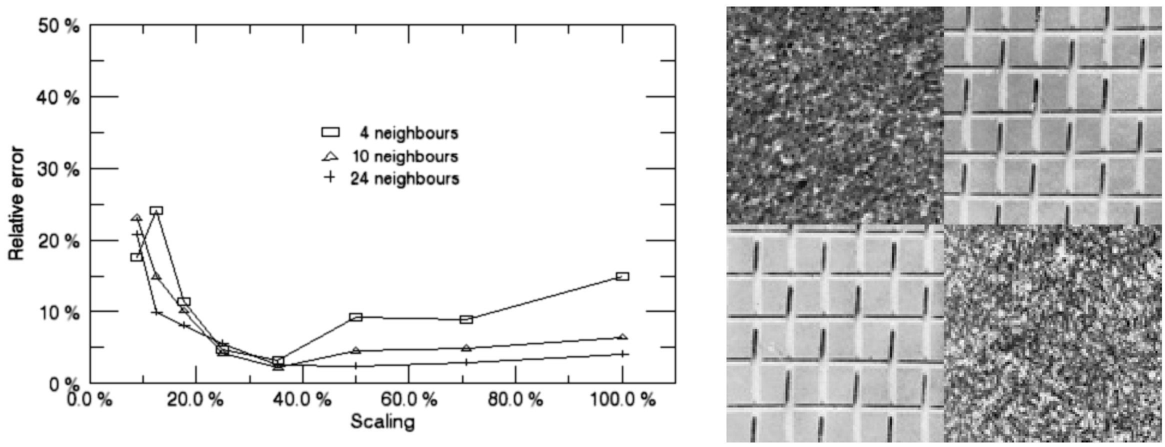

Figure 6: Example for segmentation errors with different neighbourhood systems and the segmented image

Results with aerial photos

The described methods and approaches were taken into account for segmentation of aerial photographs: the images were radiometrically normalised, the model parameters were normalised to a uniform length after extraction and a neighbourhood system with 10 neighbours was used. The segmentation was carried out for different texture window sizes and scaling.

Good results could be achieved with the used pictures when the scaling is not smaller than 50% and the texture windows are small (3-5 pixels). Nevertheless the segmentation suffers when the radiometry of the images is poor (picture in the middle). Moreover heterogeneous areas, e.g. urban areas with lot of single trees, make segmentation difficult, though in these cases a crude discrimination is possible.

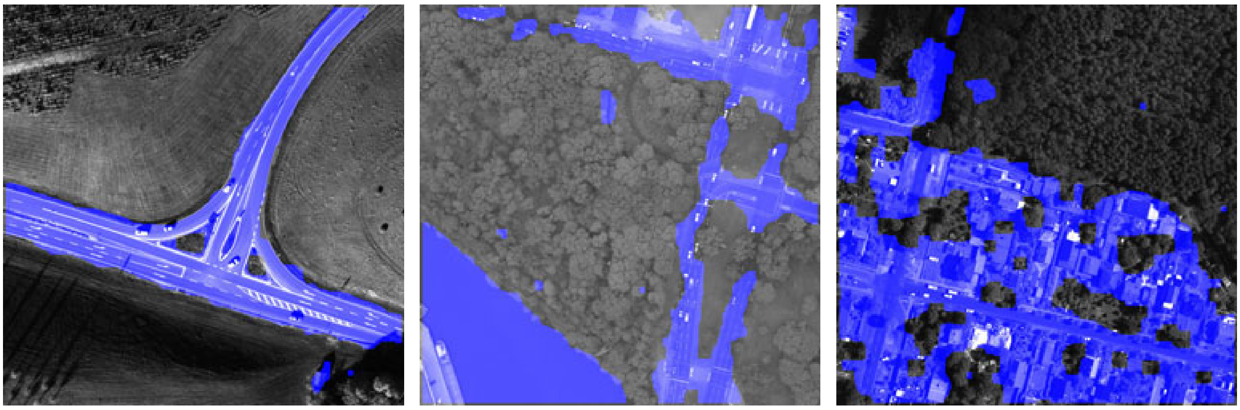

Figure 7: Segmentation results with aerial photos

CONCLUSION AND OUTLOOK

The results demonstrate the usefulness of MRFs even for demanding segmentation. However, a lot of model parameters are needed, which partially have a tremendous influence on the segmentation.

In the future other MRF models should be examined. The Gauss model seems to be more suitable. Another problem is the optimizing of the computing time of the segmentation.

ACKNOWLEDGEMENTS

Acknowledgements are made to Intergraph and DLR for making the used aerials photographs available. We would also like to thank Martin Ruhé, Ines Ernst and Matthias Hetscher for advice and assistance.

REFERENCES

i Ernst I, S Sujew, K Tiessenhuser, M Hetscher, S Raßmann & M Ruhè, 2003. LUMOS - Luftgestütztes Verkehrsmonitoring-System

ii Lippok A, 2004. Anpassung von LUMOS zur Auswertung von Satellitenbilddaten

iii Cross G, 1983. Markov Random Field Texture Models. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol PAMI-5, No. 1

iv Brodatz P, 1966. A Photographic Album of Artists and Designers (Dover Publications)

v Gimmel'farb G, 1999. Image Texture and Gibbs Random Fields (Kluwer Academic Publishers

vi Schröder M, H Rehrauer, K Seidel, M Datcu, 1998. Spatial Information Retrieval from Remote-Sensing Images – Part II: Gibbs-Markov Random Fields. IEEE Transactions on Geoscience and Remote Sensing, Vol 36, No. 5

vii Paget P, Longstaff D, 1998. Texture Synthesis via a Noncausal Nonparametric Multiscale Markov Random Field. IEEE Transactions on Image Processing, Vol 7, No. 6

viii Yue B, 2002. SAR Ice Recognition Using Texture Methods (University of Waterloo)

ix Besag J, 1986. On the Statistical Analysis of Dirty Pictures. Journal of the Royal Statistical Society, Vol B26