ANALYSIS OF URBAN STRUCTURE AND DEVELOMENT APPLYING PROCEDURES FOR AUTOMATIC MAPPING OF LARGE AREA DATA

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ABSTRACT:
For establishing sealed area mapping in urban areas, the role of NDVI is crucial but not completely understood. Normally a linear relationship is assumed. The limits of this linear model are tested and the restrictions analysed. For the various tests a hierarchical approach is chosen. Starting with the central role of texture analysis for city footprint extraction, the resulted mask is used to differentiate between *sealed* and *unsealed* areas within the city border. The degree of sealed surfaces as well as the analysis on urban sprawl is a necessity for understanding and anticipating urban change. Increasing resolution and quality of the remote sensing data are extending the capabilities of analysing urban areas with higher precision and better results. Several case studies from Magdeburg and Munich are presented in this article, showing the various scales and scale dependent themes of urban mapping ranging from extracting the city footprint from IRS pan-sharpened data up to the high precision mapping of sealed areas with IKONOS imagery. In a mixture of pixel based analysis as well as object oriented analysis, the principal objective remains with the development of automatic information extraction procedures.

1. URBAN MAPPING USING TEXTURE ANALYSIS

1.1 Successful history of texture analysis

Among imagery with higher resolution (5 meter pixel) it is easy to show high variance among neighbouring pixels in urban environment as already proven by Steinnocher (Steinnocher 1997). Texture analysis can be used as essential part of the classification procedure to establish the class of *‚build up areas'* (after Steinnocher, Köstl, 2002). Usually textural features are visualised in the image domain (after Landgrebe 1999, see also figure 1B) and practically expressed in a textural image after calculating so called Grey Level Co-occurrence Matrices. (GLCM, after Musick 1991). Urban areas then show particular local deviations within their spatial environment.

1.2 Contrast of build up areas

In West European conditions there is a natural tendency in the antropogenous affected areas to reinstall a natural vegetation cover. This tendency exist in manipulated form like agriculture practices as well as in tolerated developments in this case study visualised around the riverbeds of the Elbe (central in figure 1A). Even when homogene vegetation cover has not yet been established, e.g. fresh ploughed or harvested fields, large homogene areas are still the practical outcome of antropogenous impacts and natural developments outside settlement areas. Therefore, immediately outside a borderline of '*build up area'*, an homogeneous surrounding with or without closed vegetation cover is quite common (see also Figure 1A). The empirical conclusion from various experiments (de Kok, 2002) leads to the expectation that Landsat type imagery in West European cities expresses larger variance for albedo values in local pixels-group compared to their adjacent environment. Using local pixel variance in urban mapping is then effective in places with high homogeneity, immediately bordering those '*build up areas'*. Because of the empirical basis of this assumption, the classification rules developed for these conditions are unlikely to be transferable to areas that lack such conditions.

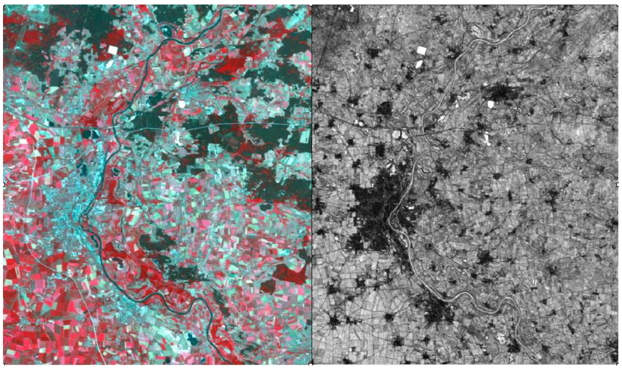


Figure 1 A-left, 1B-right, A: Pan sharpened CIR from Magdeburg/Elbe (IRS-D), B: Textural image (IDM) with high variances, shown in low-black values, here related with infrastructure.

2. BOTTLENECKS IN TEXTURE ANALYSIS

2.1 Filter-size compromise

The application of textural analysis has been hampered by the necessity to search a compromise on the filter size used in moving window procedures (Barret, Curtis, 1995; Blümel, 2000), as shown in a simplified front view in figure. Objects of interest have different characteristics when texture is calculated over various area sizes. In classical window filtering, texture analysis results in 'blobs' inside the image domain responding to a variety of textured areas (figure 3B). Although the image domain gives the impression of separability, transferring the result from the image domain to decisions in spectral domain remains problematic.

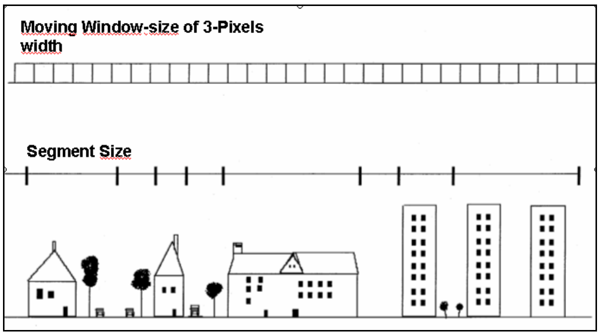


Figure 2. (after Blümel, 2000). Moving window filtering has a fixed size (here 3*3). Segment-size is varying with more than 30 pixels per object primitive.

2.2 IDM per segment

A new way of analysing texture is now available in eCognition version 3 since September 2002. The results are applied in the following analysis.

2.2.1 Manipulating area size: The moving window has a fixed area size for textural calculations. Contrary a segment (or object primitive; de Kok , 2001) adapts itself to the local environment and contains various area sizes. When calculating texture per segment after image segmentation, this compromise is moved then from selection of window size towards selection of the segmentation parameters. The various manipulations of segmentation parameters can be more adapted to objects of interest.

2.2.2 Segment based texture: As shown in figure 3C a 'homogeneity texture calculation' (also known as IDM, Steinnocher 1997) applied on segments are showing the differences between 'pure large building pixels' and their spatial environment. Also a striking example can be shown for in-homogeneities; particular dark areas showing as 'blobs' within agricultural fields (figure 3B). These 'blobs' 'dissolve' within the segments (compare figure 3B and 3C). The resulting product leads to mean grey value in agricultural areas that deviates from mean grey value within the urban areas. At the same time, outer border sharpness per agricultural parcel is maintained. This result can not be achieved in applying other techniques like focal analysis using a mean or median filter-approach.
The calculation of homogeneity per segment over larger areas results in figure 1B, showing clearly the low homogeneity response of build up area's around the city of Magdeburg (figure 3-C is a stretched detail from Figure 1B). Applying this texture-feature to large scale satellite mosaic, the resulting textural imagery shows distinctively low homogeneity for urban areas and connecting infrastructure throughout the complete mosaic (de Kok, Wever , 2002).

2.2.3 Hierarchical classification: To achieve a hierarchical classification (Holtkötter, 2002) it is useful to define first the city footprint and than proceed to classification of areas within the city-footprint. By using the footprint as a mask, spectral confusion, which causes overlap with non-urban classes can be excluded beforehand.

2.2.4 Essential textural analysis: The analysis of texture per segment is a crucial element in the automatic extraction of the city footprint. The city footprint lies at the basis of further urban analysis. For change detection, the changes of the city footprint are useful indicators for the classical urban sprawl where urban extension is spatially close to existing city-footprint edges.

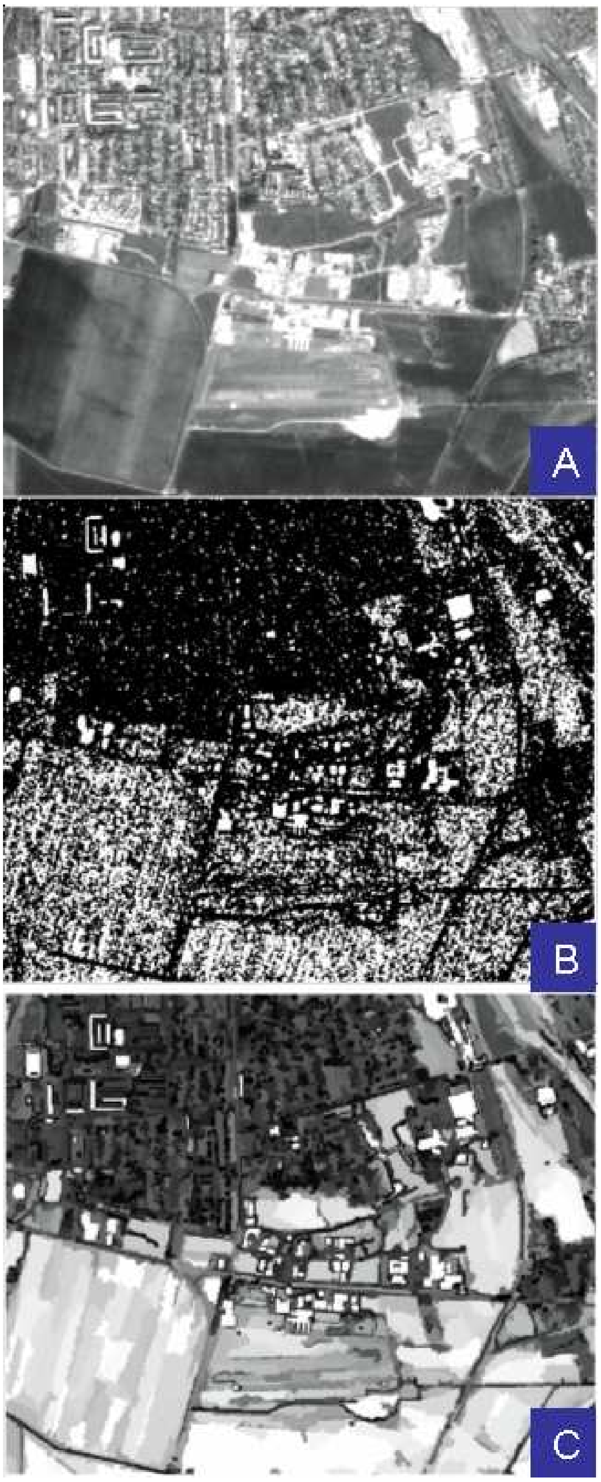


Figure 3 A-top,B-middle,C-below; A: Magdeburg-south Principle-Component 1 (derived from IRS-Pan sharpened image 5 meter), B; Moving Window IDM (3*3) texture-calculation; C: Segment based IDM texture-calculation.

For modern urban sprawl, which follows highway and especially highway entrance/exit areas, a textural difference analysis shows also the areas not directly linked to city footprint.

2.2.5 City footprint accuracy: Using texture for city footprint extraction has successfully developed since Steinnocher's GLCM analysis using IRS data (Steinnocher, 1997). To test the quality assessment, the automatic detected city footprint has been compared with a visual interpretation on a 1.25.000 scale (TK25 combined with 5 meter pan sharpen IRS-mosaic data).

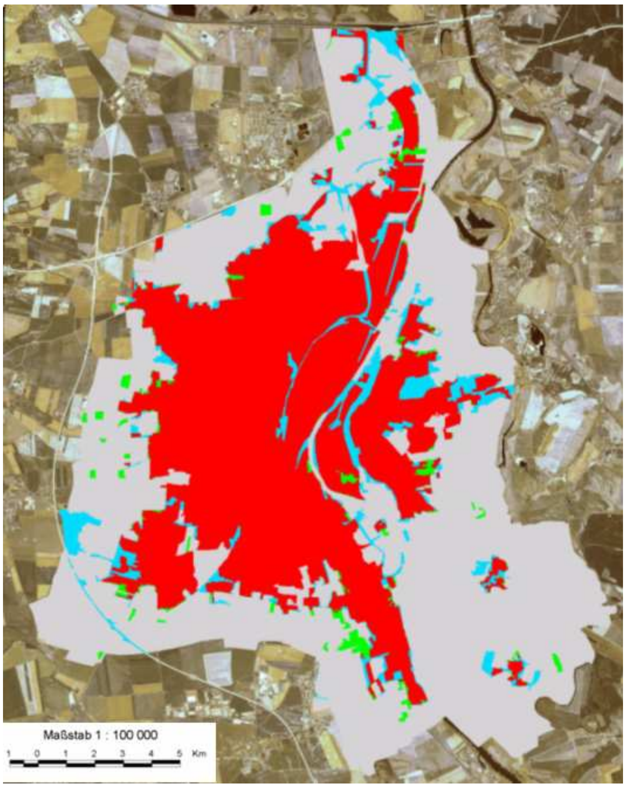


Figure 4: City-footprint Magdeburg; Red: similar to visual interpretation, Green: only in the visual int., Cyan: only in automatic extraction, Grey: border of municipality

The similarity of area cover between automatic and visual extraction reaches 83 % (see Figure 4). This is a higher score than reached in a standard product like CORINE_2000 (european topic centre, 2000). The deviations with visual interpretation can not immediately be interpreted as 'failures'. For example, large construction areas close to highway-connections are showing open soil and building-pits. These are registered by automatic detection but are not included in the visual interpretation of build up areas.

3. NDVI AND SEALED AREAS

3.1 Linear dependencies

Important in urban analysis is the mapping of sealed areas (Schallenberg, 2001). As reported in literature (Esch, 2003), a linear dependency can be expected between degree of sealing and the NDVI value within German city environment.
To test the linear dependency between NDVI value for Landsat type data and degree of surface sealing, a reference map was created from IKONOS imagery recorded over Munich (3-9-2001).

3.2 IKONOS binarization

Vegetation and the related NDVI-values are most representative for non-sealed areas within the city footprint. An IKONOS masked area for example shows high NDVI values in garden and park structures (Figure 5A). Few areas, such as construction sides are unsealed and have no vegetation.
The automatic IKONOS binarization with 2 classes (0-sealed; 1 non-sealed, figure 5C), was first compared with a visual interpretation of the data (shown In figure 5B). A similarity of 84% was recorded in the comparison of the datasets (red and green in 5D). A large part of the differences could be located within the shadow surfaces which can make up to 15 % of the areas within the city surface (Pilz, 2000). Because NDVI values can be measured within the shadow areas using IKONOS 11-bit data, it can be assumed that the sealed surface mapping using IKONOS data exceeds the 90% accuracy when no differentiation in sealed areas is taken in consideration (e.g. degree of sealing for asphalt versus cobble-stone etc. The areas are regarded completely sealed). For better calibration of IKONOS data, the 'ground truth' can only be retrieved from LIDAR data or local field measurement.

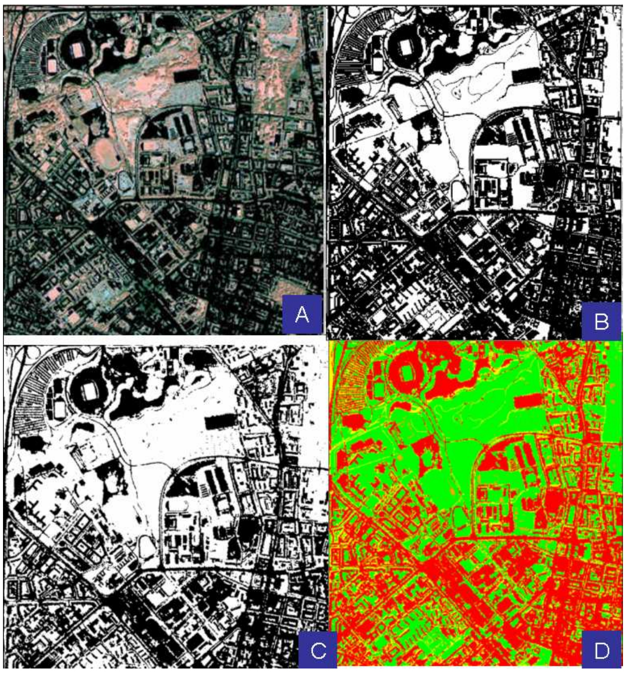


Figure 5 A,B,C,D; ***Schedule:***

5A; IKONOS CIR image for unsealed surfaces only (masked with binarized sealed/unsealed~ 0/1 mask)	5B; Visual digitized unsealed surfaces (white)
5C: Automatic extracted unsealed surfaces	5D; Comparing B and C , Red~both unsealed; Green~both sealed; Yellow and Orange~ differences (less than 16%)

3.3 Artificial Mixed pixel analysis

To compare a single SPOT5 pixel of 100m² with IKONOS, the IKONOS 1-meter pixels have to be resampled. The degrading process of IKONOS uses effectively a 10*10 window and calculates the mean of this 100m². The binarized IKONOS original is set in such a way that a pure sealed pixel (of 100m²) was assigned the value 100 and a pure unsealed pixel a value of

0 (the latter where all 100 pixels within 10*10 meter have a value of 0). This method also creates artificial ‘mixed pixels’ which simulate SPOT5 imaging data. To compensate for geometric errors, the following assumption was introduced; Values between 6 and 94 are belonging to ‘real mixed pixels’. Values 0 to 5 belonging to unsealed surface and from 95 to 100 to sealed surfaces, the original SPOT-5 NDVI values can be separated in 3 classes (see figure 6). Curious to observe that the class *unsealed* and *sealed* together (red and black in figure 7) contains 71% of all pixels.

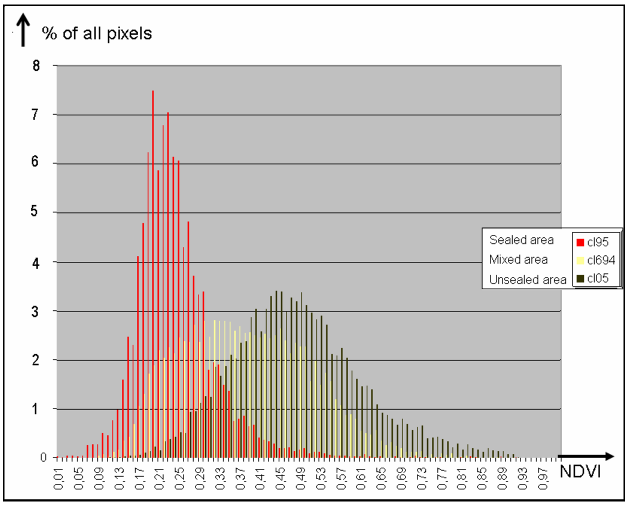
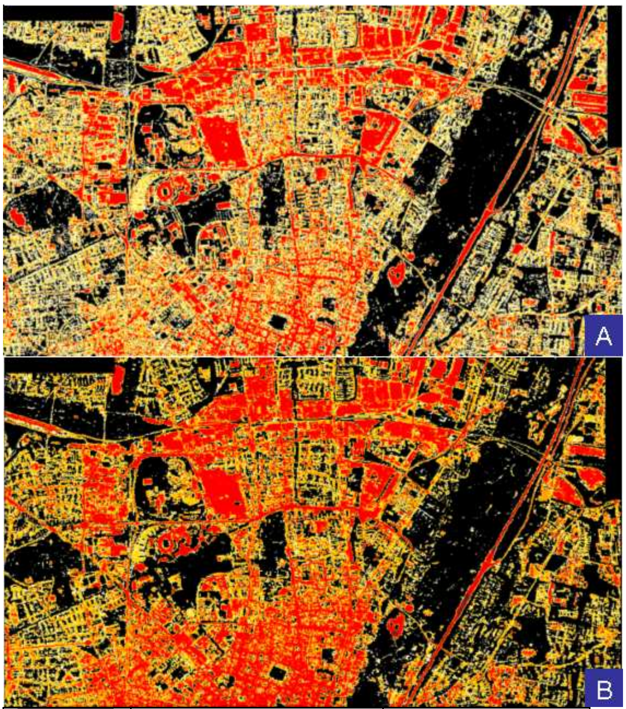


Figure 6: **Pixel level**. Two histograms for ‘pure pixels’ and one for mixed pixels;
x-axis=NDVI value from SPOT5. Pure sealed area in red (values in degraded IKONOS ranging from 95-100), Pure unsealed area in black (values 0-5). Mixed pixels in yellow (values 6- 94).

Starting with the assumption, that the IKONOS imagery is ‘perfect’, the linear relationship between NDVI value and sealed surface can not be easily applied. First of all, 71% of all SPOT5 pixels are pure pixels in the sense that they belong to sealed or unsealed surfaces. So linear relationship should be applied only to 29% ‘mixed pixels’. However the mixed pixels are divided in those originating from shadow areas with low infrared values and those with high infrared values. Possibly, the mixed pixels that are affected by shadow should be tested against an offset. If NDVI in shadow is higher than the lowest value in green histogram (figure 6, value 0.12), shadow should belong to unsealed area. With around 15% shadow area, linear relationship can only be expected for around 15% of all pixels in SPOT 5 imagery within the test area.

For a first test, the sealed area of the degraded IKONOS imagery was reclassified in 5 classes according to the degree of sealing (figure 7A).
Visual adapting SPOT5 imagery towards this result (figure 7B) does not reveals exact how the relationship between NDVI and sealed surface functions. The breakpoints necessary to simulate the IKONOS master-map are varying over the complete 8-bit range of original NDVI values. A more complex analysis is needed at this point.



	80-100% sealed 60-80% sealed 40-60% sealed 20-40% sealed 0-20% sealed	Figure 7A,B A:IKONOS-top B: SPOT 5-below Sealed area in central Munich

3.4 Combining city_footprint and sealed surface

The breakpoints used for Figure 7B can be extended to the complete Munich citymap regarding the area within the city footprint. This results in figure 8.

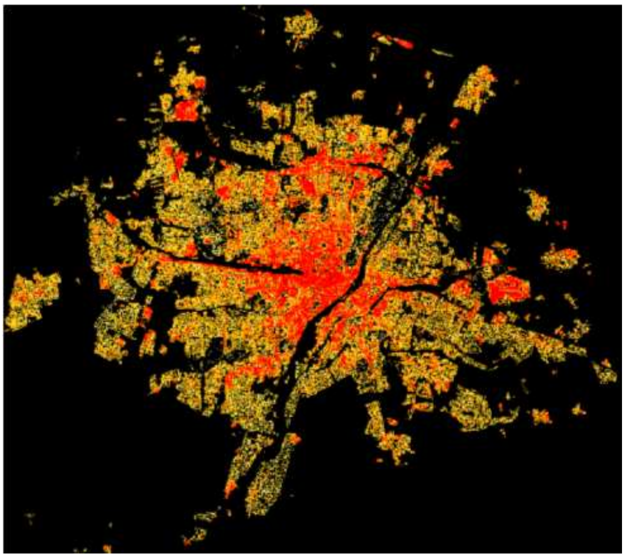


Figure 8: SPOT5, sealed area image inside the city-footprint of Munich

4. CONCLUDING REMARKS

4.1 Hierarchical classification

Texture analysis inside object primitives is a stable and transferable feature of object primitives, (deKok, 2002) which boost the quality of delineation and classification of cityfootprint extraction over large areas that show similar conditions as those available in West Europe. The manipulation of segment size makes the application of Grey-Level Co-occurances textural features easier applicable for a large variety of objects of interest and leads to a 100% detection of all large cities in the satellite-mosaic, however with less than 85% delineation accuracy. This first delineation is the first steptowards a hierarchical classification as shown for sealed area maps. A sealed area map from VHR data (IKONOS imagery) can be presented as binarized in the class *sealed* or *unsealed*. For this result (figure 5C) no linear relationship has been assumed between NDVI and degree of sealing. The assumption of non-differentiation of sealed area type such as asphalt or cobblestone is a rough simplification of traditional photogrammetrical standards for sealed area mapping (after Pilz, 2001). The differentiation can hardly be achieved with IKONOS imagery. Mixed pixel analysis shows that about 29% SPOT5-pixels belong to the mixed pixel class. This leads to the conclusion that the majority of all pixels in a SPOT5 image in urban areas belong to pure sealed and unsealed pixels for which linear relationship between NDVI and degree of sealing does not hold. To subdivide the mixed pixels, first shadow candidates should be separated from the rest. Those can make up to 15% of all inner-city pixels. Only for the remaining mixed pixels the linear relationship might be applicable.

4.2 Necessary conditions

As a better model can not be offered from this study alone, the first model for the relationship NDVI and sealed surfaces must remain the linear relationship. The final sealed area-map from SPOT and/or IRS imagery must contain;

1. A high percentage of pure sealed and pure unsealed area's
2. A visualization of the linear structure typical for sealed areas in the initial classified map. This should be still the case, even when smoothing or filtering results in large area polygons in the final output.
3. A separation of shadow areas in shadows from trees and shadows from buildings.

Sealed surface mapping for SPOT imagery shows to be more complex than assumed. The linear model for NDVI and sealed surface should be applied with care.

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