HYPERSPECTRAL MEETS LASERSCANNING: IMAGE ANALYSIS OF ROOF SURFACES

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ABSTRACT:

Description of roofs in urban environments by their geometry and material is a basic feature for budgeting toxic water runoff. This e.g. allows to quantify pollution and the necessary dimension of sewage plants.

An automatic procedure to determine the roof parameters has been jointly developed by geodesists and water chemistry experts from Karlsruhe University. Input data are hyperspectral images together with airborne laserscanning data. Image segmentation and classification use mainly the object-oriented eCognition approach. The procedure was tested at the Karlsruhe University Campus as a pilot area. For five main roof surface classes (brick, copper, aluminium/zinc, slate and stonelike/bitumen) the obtained absolute accuracy is better than 90 %.

1. 1. INTRODUCTION

The ongoing dynamic development of sensor technology leads to completely new opportunities and applications in the GIS domain: This confirms the technological law that new tools should not focus on existing products, but must necessarily lead to new ones. In this context, the paper presents a new opportunity offered by fusion of high resolution sensors, i.e. laserscanning on the one hand and hyperspectral imagery on the other. Both feature high-resolution: laser scanning with respect to its geometrical resolution and hyperspectral imagery with respect to its inherent spectral resolution in terms of the number of narrow bands represented.

The new opportunity given here is the description of roof surfaces by dimension and material in order to quantify polluted runoff water. Roofs in urban area had already played a role for 3D City models however limited to geometry (cf. Baltsavias and Grün, 2001). The analysis for pollution of runoff water is a new challenge. Functionality of roof surfaces has been neglected so far for both their negative and positive impact. While a negative side is presented in the following investigation, a positive side would be the use of roof surfaces for photovoltaic mini power plant assembly.

2. BACKGROUND OF THE INVESTIGATION

Laser scanning and hyperspectral data are often used exclusively, either to derive the geometry based on laser scanning data (cf. [2]) or to derive material maps based on hyperspectral data (cf. [1]). [3] use hyperspectral data (AVIRIS) in order to improve reconstruction results based on IFSAR, namely to mask vegetation areas, but the used data has only limited geometric resolution. In [4], they present results of hyperspectral data analysis for urban areas based on ROSIS and DAIS data, also discussing the impact of spectral and geometric resolution. [5] integrate Digital Surface Model (DSM) information in order to improve the results of hyperspectral classification based on HYDICE data. In their research the DSM, derived from aerial imagery, is applied for the discrimination of roofs and ground surfaces. The materials may have a similar spectrum, but they can be discriminated based on the height information. [6] show material mapping techniques based on deterministic similarity measures for spectral matching to separate target from non-target pixels in urban areas.
[7] is the closest related work to our approach. They use a normalized DSM and hyperspectral data taken by the airborne DAIS 7915 sensor. A similar approach of [8] is using HyMap data, high resolution orthophotos and a DSM – the latter both derived from HRSC-A data. Their focus is on fusing the high resolution datasets by a segment-based technique.
Our approach differs from the above with respect to the input data, in particular the laser scanning data. The segmentation strategy used allows to incorporate geometric and spectral clues. For classification, we use eCognition, which allows a hierchical classification and introduction of knowledge by using the different information sources for different decisions within a fuzzy classification scheme.
The given results are from a research project under way at Karlsruhe University in cooperation with the Chair of Water Chemistry (Engler-Bunte-Institute) and the Institute of Photogrammetry and Remote Sensing. The aim is to quantify pollution from sealed surfaces in urban environment, especially from the different kind of roof surfaces and their different materials. The toxic material, like the metallic surfaces, has a strong impact on the type and dimension of sewage plants. The question is discussed, whether the owner of a building, that produces pollution and the cost to remove it, should pay a tax. On the other hand, treatment of rain runoffs water would be easier and considerably cheaper in case of low pollution rates. The modelling of the dissolved harmful components is not a trivial matter. Experiments in the Labs of Water Chemistry show a function of rainfall characteristics, different for the respective material. First flush shows higher concentrations than the following run off. After all, the concentrations are in function of the time elapsed from the last rainfall event.

The recent activities in the described field emerge last not least from the EU water framework directive, which require continuous monitoring of the status for surface and ground water. Table 1 gives an overview of common roof material and their contribution to pollution.

Material	Pollutant
Brick	PAC
Copper	CU, PAC
Aluminium	
Zinc	ZN, PAC
Roofing felt/Bitumen	TOC, DOC
Stone plates, gravel	
Slate	
Grass	

Table 1: Example of roof materials and their properties as pollutants

The definition of classes must take into consideration that stone plates and gravel are always combined with bitumen, and aluminium and zinc may not be separated even from visual inspection (see chapter 4).

3. PILOT AREA AND DATA

The Campus of Karlsruhe University was taken for a pilot area. The nearly 200 years of age of this oldest German Technical University show large roof surfaces of different material. The buildings, where the roofs are all accessible for checking without difficulties, are concentrated in an area of approximately 1 km x 0,5 km. The Campus is very well suited as a training field for research activities. A photogrammetric CAD-Model is available for multipurpose use together with sets of roof material from local inspection (Figure 1).

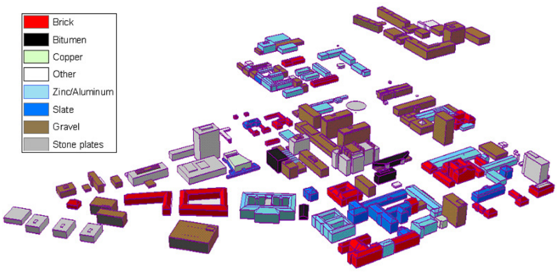

Figure 1: The main campus of Karlsruhe University (approx. 1km x 0.5 km)
CAD model generated from aerial photogrammetry

The roof material of all buildings has been checked during the photogrammetric restitution by data from the University Administration and/or by local inspection. This yields nearly perfect ground truth.

Table 2 resumes the hyperspectral data together with the laser scanning flight (more details see [12]).

PAC = Polycyclic aromatic components, TOC = Total organic carbon, DOC = Dissolved organic carbon, Cu = copper, Zn = Zinc

Sensor	HyMap	TopoSys II
Flight	HyEurope Campaign 07/2003	March, 2002
Operation and Data preprocessing	DLR (German Aerospace Centre)	TopoSys Company Ravensburg
Ground Resolution	4 m x 4 m (1m x 1m resampling)	1m x 1m
Spectral Range	438 – 2483 nm	1560 nm (*)
Spectral Resolution	126 channels	1 channel
Mode		First and last pulse

Table 2: Airborne hyperspectral and laser scanning data (*) used wavelength

4. METHODOLOGY

The classification of roof surfaces in urban environment requires high-resolution data for both geometric and spectral properties as shown in the previous chapter. Due to the very complex urban scenario (see Fig. 2), the object-based eCognition approach was chosen. This is an explicit procedure, where knowledge is entered a priori (a so-called “knowledge based approach”). The more heuristic statistical methods, like a Maximum Likelihood Multispectral Classification is not applicable, because of restriction to spectral signatures in a complex large scale environment.

Figure 2: Geometrical and spectral challenges in a large scale urbain domain (section of approx. 100m x 100m from the central campus).

4.1 Image Segmentation

Image segmentation means subdivision of the scene into homogeneous primitives which are useful for the subsequent classification. In our case we are looking for roofs and their material, i. e. planar surfaces of different slope and of height above the ground starting from 3 m approximately.

The eCognition software, designed for Remote Sensing applications, does not allow to accept inclined surfaces as homogeneous by its region growing algorithm. However, inclination is a very strong geometric property entered from laserscanning data. Therefore, by IPF an algorithm was developed (first by F. Quint and S. Landes, 1996 [10] and refined by T. Vögtle and E. Steinle, 2000 [11]), which allows the segmentation of inclined roofs. Figures 3a/b show the obtained improvement for roofs.

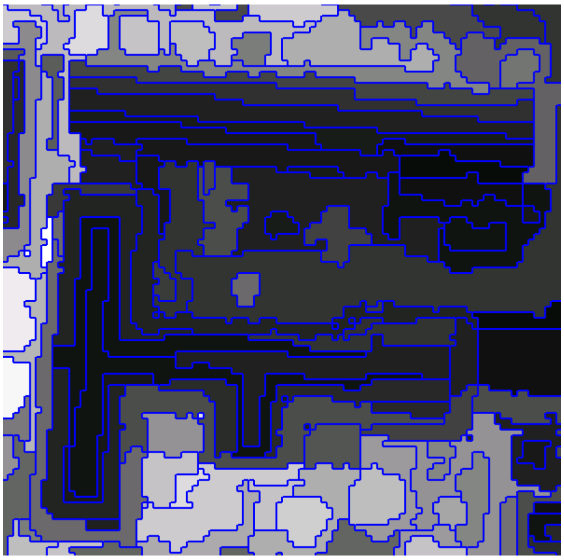

Fig. 3a: Segmentation of homogeneous primitives by eCognition (same clipping as Fig. 2)

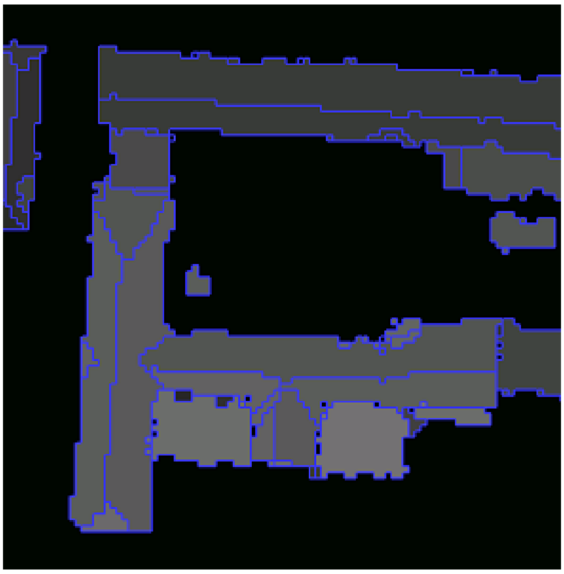

Fig. 3b: Segmentation of homogeneous primitives by the IPF approach

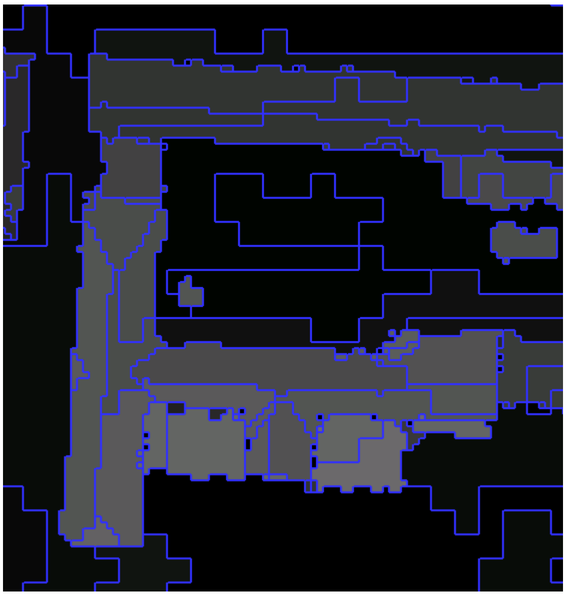

Fig. 3c: IPF approach followed by eCognition

The smooth transition between the brick and the slate patch at the lower right of Fig. 3 cannot be resolved by the geometric segmentation. Therefore, a subsequent eCognition algorithm had to be applied taking 2 spectral channels (red and infrared) in addition to the "geometric" ones from laserscanning.

This procedure leads to the results shown in Fig. 3c. The roof surfaces are correctly separated. Consequently this 2step-approach for segmentation is applied for the entire scene and offers an augmented functionality.

4.2 Classification

The definition of classes has to be done in relation to their contribution to the budget of pollution on the one hand side and to the available data in the feature space on the other. As mentioned before (chapter 2), stone plates, gravel and bitumen/roofing felt are assigned to one class "stonelike/bitumen", because stone plates and gravel on roofs only occur in combination with bitumen underneath the surface, thus producing the respective toxic components. Moreover, zinc and aluminium are aggregated to one class after classification.

The feature space offers geometric parameters from the laserscanning and spectral ones from the hyperspectral flight. 3 geometrical channels are applied (i. e. heights from first and last pulse together with slope) and 20 spectral channels carefully selected out of the available 126 Hymap channels. Figure 4 gives an overview of the spectra for the roof material under consideration.

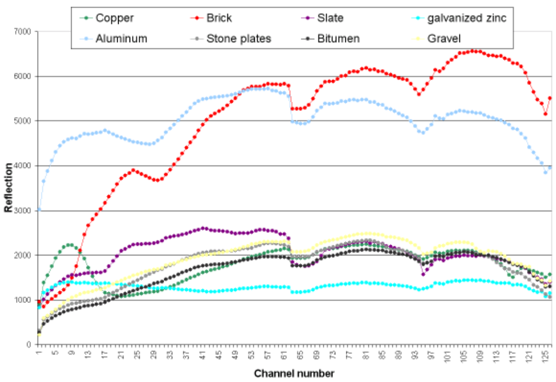

Figure 4: Spectra of roof surfaces (directly taken from the real HyMap data set)

The eCognition fuzzy logic based classification procedure requires the a priori estimation of membership functions for each class. By this step knowledge about the classes with respect to the geometric and spectral features is modelled. This includes, besides obvious conclusions (e. g. steep increase of the brick spectral curve from channel 1 to 25, see Figure 4), more sophisticated relations are considered: Slope of the roof surfaces may serve as a class indicator. Flat roofs are always connected with stone plates/gravel/bitumen; in case of brick and slate an inclination is mandatory.

5. RESULTS

Tests have been done for different compositions of the input features for classification and reported by D. Lemp and U. Weidner (2005) [12]. In conclusion, refined segmentation and classification pays off and lead to better results compared to less rigorous approaches.

5.1 Roof maps

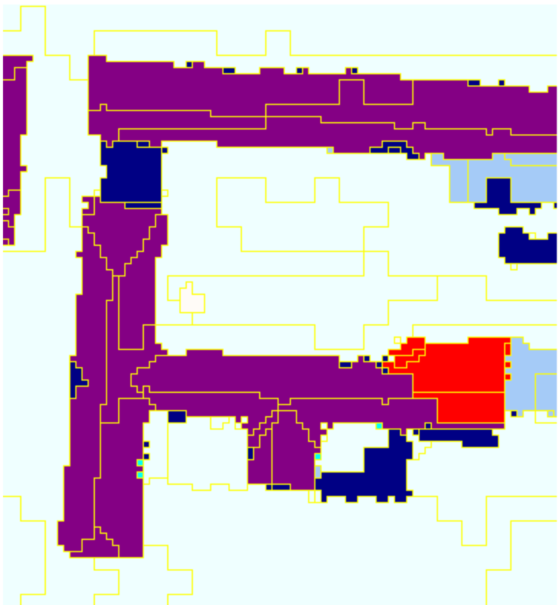
Figure 5: Classification result for the example of Figure 2/3 (legend see Figure 4)

Figure 5 shows the classification result for the small central campus section introduced in Figure 2. Visual inspection comparing Figure 2 and Figure 5 reveals a good quality of the result, taking in consideration the very complex building topography.

The membership values in the classification procedure were determined by the *fuzzy and (min),* which showed a better quality than the *fuzzy or (max).* More details concerning the classification procedure are given in [9].

The approach was applied to the whole area of the University Campus (Figure 1) and adjacent areas. The complete result (73.659 m^2) is displayed in [12]. With respect to a better readability, Figure 6 restricts the resulting roof map to the central part of the main campus.

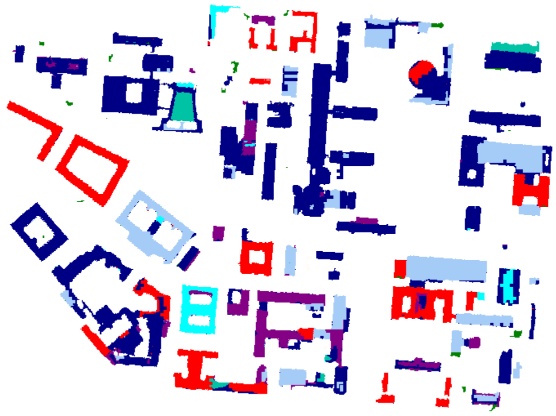
Figure 6: Final result: roof map of the Karlsruhe University (enlarged section approximately 0,8 km x 0,5 km, legend see Figure 4).

5.2 Quality Assessment

Quality check of classification is a crucial step in image analysis. This is particularly true for the implicit methods, where knowledge is not modelled a priori. In case of knowledge-based explicit approaches like fuzzy logic in eCognition, the system itself offers internal quality measures.

In this context the eCognition software takes the membership values as a “stability factor”. The values are computed for each object in the respective classes and present individual estimations of the reliability of the obtained results.

Class	Objects	Mean	StdDev	Minimum	Maximum
brick	1380	0.933	0.178	0	1
copper	63	0.9	0.241	0	1
Aluminum	413	0.835	0.302	0	1
slate	222	0.703	0.275	0	0.999
stone like	1674	0.878	0.227	0.000785	1
galvanized metal (zinc sheet)	75	0.837	0.307	0.0134	1

Table 3: Mean membership values and their statistics for all objects retrieved for the *fuzzy and (min)*

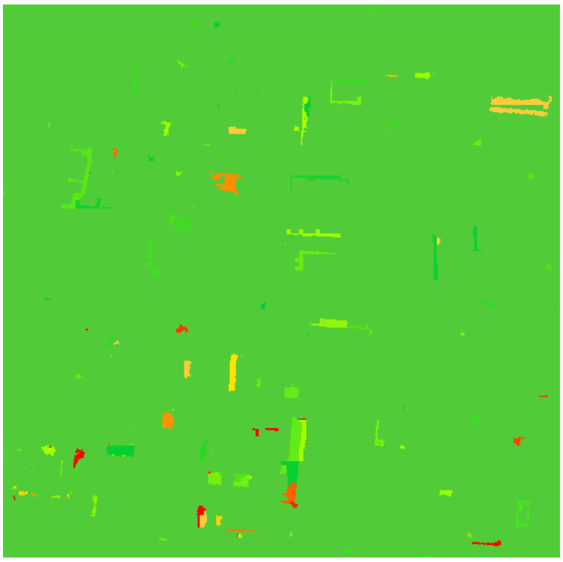

Figure 7: eCognition stability of classification for the area displayed in Fig. 6

The statistics of Table 3 shows high membership values for all classes. However, visualisation of the individual results in Fig. 7 reveal that in some minor areas the stability is weak. This happens primarily due to the limited geometrical ground resolution of 4m x 4m for the HyMap system which is not fully acceptable for roof analysis.

As mentioned earlier, ground truth from local inspection is available. Therefore, this reference may be compared to the obtained results from eCognition leading to absolute quality values. In Table 4 the comparison is given by a confusion matrix. The numbers confirm the results from the previous analysis (Table 3 and Figure 7), showing best quality for brick roofs (nearly 100% correct classification) and the weakest for slate roofs. The overall correctness is 91,2%, i.e. 67.167 m^2 out of 73.659 m^2 were correctly classified.

Reference ⇨ eCognition ⇩	brick	copper	aluminum/ zinc (*)	slate	stonelike/ bitumen	consumer accuracy
brick	**12728**	0	8	0	6	99.9%
copper	0	**1570**	111	0	7	93%
aluminum/zinc	0	106	**14810**	232	2169	85.5%
slate	24	0	410	**4490**	634	81%
stonelike/bitumen	76	99	732	356	**33569**	96.4%
producer accuracy	99.2%	88.5%	92.2%	88.4%	92.3%	

Table 4: Confusion matrix comparing reference data (ground truth) to object-oriented classification results The numbers are in m^2
(*) Aluminum and Zinc is not seperated yet in reference data

6. OUTLOOK

New sensors like airborne hyperspectral and laserscanning lead to new applications, requiring new models and algorithms. The joint processing of hyperspectral and laserscanning means the fusion of very different data types. Therefore, the object oriented eCognition approach is well suited in order to obtain satisfactory results: finally a budget of pollution for runoff water from roofs.

Large scale applications in urban environments will show growing importance in future. The reasons are in the demographic development, exploding population and megacities with all their problems like pollution, traffic collapse or disasters. Roofs as pollutants represent a very small sector in this context; however, they may be regarded also as resources. This is, e.g., true for installation of photovoltaic mini power plants on roof surfaces. The necessary methodology to find appropriate locations would be very similar to what has been developed in the presented analysis.

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