IMPROVEMENTS OF ROOF SURFACE CLASSIFICATION USING HYPERSPECTRAL AND LASER SCANNING DATA

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ABSTRACT:

The quantitative assessment of pollutants on urban surfaces is of high economical and ecological interest. Nowadays a better part of the rain water from sealed urban surfaces is treated in sewage plants, although this might not be necessary regarding economical aspects and not desirable regarding ecological considerations, because the load of pollutants of the first flush is much higher than in the following run-off. Therefore, the dimensioning of sewage systems and on-site preflooders may be adopted to this observation and costs may be reduced as well as a subsidence of the groundwater table could be prevented, if unpolluted rainwater is discharged to the groundwater. While the focus of the Engler-Bunte-Institute (EBI), chair of water chemistry, is on the chemical analysis of the rain run-offs, the Institute of Photogrammetry and Remote Sensing (IPF) aims at the characterization of urban roof surfaces, namely their geometry (slope, exposition, size) and their surface material. For this purpose hyperspectral data with high spectral resolution and laser scanning data with high geometric resolution are combined to create a detailed map of these surfaces.
In Lemp and Weidner (2004) we already presented first results of our approach based on segmentation using eCognition and a previously presented technique from IPF for segmentation of roof surface patches. The classification of materials using eCognition was solely based on the hyperspectral data. In our recent developments we extend this approach by using the slope information, because of the correlation of roof slope and possible surface materials. For the classification we apply eCognition which allows the introduction of this knowledge as well as the use of detailed spectral properties within a fuzzy classification scheme. This increases the separability of classes with similar spectra but different geometrical attributes. The paper presents new aspects of segmentation, classification and results of data analysis, which will be focused on roof surfaces.

1. INTRODUCTION

Due to a regulation of the EU water framework directive, the influence of human activity on the status of surface waters and groundwater has to be reviewed by each member state. The assessment of pollutants on urban surfaces and their impact on the pollution load in rain runoffs is a small, but nevertheless important topic in this context.
Thus, one aim of a recent project is not only to derive information on the amount of sealed surfaces in an urban area (cf. Butz and Fuchs (2003)), but also to derive a detailed surface material map. Chemical measurements for the characterization of the chemical processes on reference roof surfaces are defining the framwork of classes within the classification of roof surface materials. Many roof constructions have similar polluting behaviour resulting from a not visible bitumen layer, while they show differences in spectral properties of their surface. The material-oriented identification (cf. Heiden et al. (2001)) leading to a detailed material map is supported by geometric clues of surface patches. Furthermore in our application, classes with different spectral characteristics may be merged with respect to the resulting pollution.
Urban areas are characterized by their complex geometric structure and their heterogenity concerning the occuring surface materials. The appearance of surface patches' materials in the data is influenced by the acquisition and object geometry. Also the collection of rain runoffs is dependent on the slope and exposition of roof segments. Furthermore, the age of the material and environmental conditions, e.g. by weathering and humidity, also have impact on their appearance. All these facts lead to the necessity of high resolution input data to solve the tasks – high resolution with respect to the geometric resolution, but also to the spectral resolution in order to discriminate the various surface materials. Therefore, we combine data derived from laser scanning, which provides the necessary geometric information, and hyperspectral data for the spectral analysis of surface materials.

In the following, we give a short overview on related work dealing with the use and combination of laser scanning and hyperspectral data. Section 3 introduces the input data. Our approach for the characterization of surfaces in urban areas is presented in Section 4 focussing on roof surfaces. A summary of recent results as well as a qualitative comparison of our results with a reference data set follows in Section 5 and the conclusions.

2. RELATED WORK

Up to now, the laser scanning and hyperspectral data were often used exclusively, either to derive the geometry based on laser scanning data (cf. Vögtle and Steinle (2003)) or to derive material maps based on hyperspectral data (cf. Heiden et al. (2001)). The improvement of reconstruction from laser data by additional image information is discussed, but mainly to reject vegetation areas. Gamba and Houshmand (2000) 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. Madhok and Landgrebe, (1999) integrate 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. Homayouni and Roux (2004) show material mapping techniques based on deterministic similarity measures for spectral matching to separate targets from non target pixels in urban areas.

Bochow et al. (2003) is the closest related work to our approach. They use a normalized Digital Surface Model (nDSM) approximating the ground surface and hyperspectral data taken by the airborne DAIS 7915 sensor. A similar approach of Greiwe et al. (2004) is using HyMap data and high resolution orthophotos and a surface model 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 aboves with respect to the input data, in particular the laser scanning data. The development of special segmentation algorithms allows the consideration of multiple geometric characteristics, e.g. slope and size of surface patches. We use eCognition for classification of the data, which allows a hierchical classification and introduction of knowledge by using the different information sources for different decisions within a fuzzy classification scheme. Details are given in Section 4.

3. DATA

For the characterization of urban surfaces with respect to their geometry and their materials, two different data sets are combined: a DSM and hyperspectral data. The DSM was acquired in March, 2002, with the TopoSys system using the first (cf. Fig. 1) and the last pulse modes. For ease of use within different software packages, 1 m × 1 m raster data sets were generated. These data sets differ not only concerning the objects included, but also showing systematic effects: surface patches appear smoother and building footprints are systematically smaller in the last pulse data. The impact of these differences on the analysis was discussed in Lemp and Weidner (2004).
The hyperspectral data was acquired in July, 2003, with the HyMap sensor during the HyEurope campaign organized by the DLR (German Aerospace Center). Figure 2 displays a band combination ranging from the visible to the near infrared spectrum. The white line indicates the central campus area. The data was preprocessed (atmospheric corrections, geocoding) by the DLR, Oberpfaffenhofen, using the DSM. The original data has a ground resolution of 4 m × 4 m. In order to use the data in combination with the DSM, the data was resampled to a resolution of 1 m × 1 m using nearest-neighbour interpolation (cf. Lemp and Weidner (2004)). For the classification we applied a manual selection of bands based on the spectra of selected surface materials (Fig. 4). The classification results are compared, using ArcGIS software, with a 3D campus model (Fig. 3) as reference data, which was generated from aerial images taken in spring, 2002. Further details are given in Section 5.

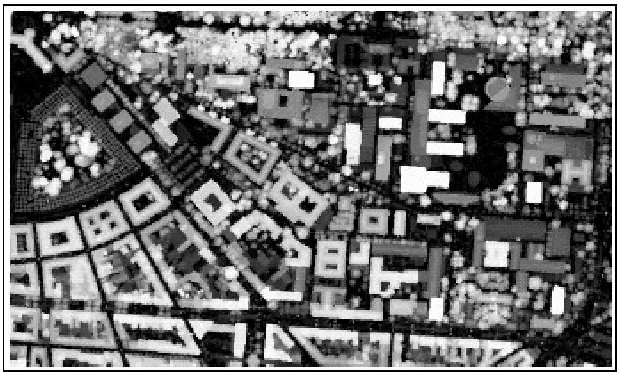


Figure 1: nDSM from laser data (first pulse mode)

Figure 2: Hyperspectral data (RGB=25/15/10)

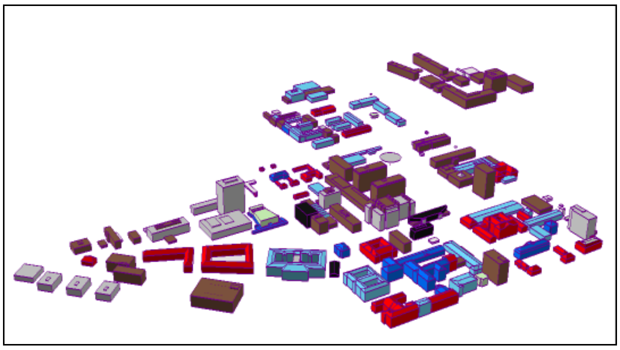


Figure 3: 3D-campus model generated from aerial pictures

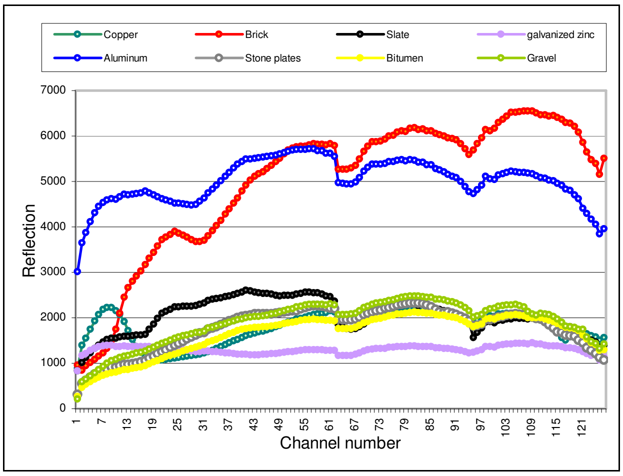


Figure 4: Spectra of selected surface materials

4. DATA ANALYSIS

The characterization of urban surfaces is based on the analysis of laser scanning and hyperspectral data as already depicted in Lemp and Weidner (2004). The geometry of surface patches is derived using a DSM from laser scanning, whereas the surface material information is obtained from both, laser scanning and hyperspectral data.

With respect to the demands of our project (the chemical analysis of rain runoffs) the classification focus is not only on the material and geometry itself, but also on the detection and balance of contained pollutants. In some cases these ambitions ease requirements on the classification – e.g. in the majority of cases flat roofs are consisting of a bitumen sealing with a variable upper layer of gravel, stone plates or other stonelike materials. In such cases bitumen seems to have the main influence on pollution while the stone cover is of minor importance and a separation in different classes is not nessessary. Observing this fact, three categories bitumen, stone plates and gravel could be joined to one class “stonelike/bitumen”. On the other hand the need of a more detailed separation of metal surfaces to galvanized metal (zinc), and aluminum was realized. Table 1 shows some examples of roof surface characteristics, grouped with respect to similar spectra, and also indicating qualitatively the surface geometry. Taking the properties into account, the slope information is used as additional clue within the classification in case of slate and “stonelike/bitumen”, which show a high spectral similarity (see Fig. 4).

The data analysis is structured in two main parts, namely (1) the geometrical segmentation using either eCognition or an IPF algorithm, and (2) the spectral segmentation and classification using the software package eCognition. The quality of segmentation is crucial as it impacts directly the classification result. In the following, we describe segmentation and classification in detail using a subset of the data as example.

material	**geometry**			**pollutant**	**remarks**
	flat	**slope <10%**	**slope >10%**	(*)	
Brick	-	+	++	PAC	
Copper	-	+	+	Cu, PAC	
Aluminum	-	++	+		
Zinc	-	+	++	Zn, PAC	
Roofing felt/ Bitumen	++	+	+	TOC DOC	Joined to class “stonelike/ bitumen”
Stone plates	++	-	-	TOC DOC	Joined to class “stonelike/ bitumen”
Gravel	++	-	-	TOC DOC	Joined to class “stonelike/ bitumen”
Slate	-	+	+		spectrum similar to class “stonelike/ bitumen”
Grass	+	+	-		limited slope

Table 1: Examples of roof surface characteristics

(*): PAC = Polycyclic aromatic compounds, Cu = copper, Zn = zinc, TOC = total organic carbon, DOC = dissolved organic carbon

4.1 Segmentation

The segmentation procedure within the eCognition software is based on a region growing algorithm. The criterion for the growing combines three different quantities: the homogeneity of the segment, the shape of the segment measured by its compactness, and the smoothness of its boundary. The homogeneity of the segment takes the deviations from the mean of each channel used for segmentation into account. Thus, the underlying model assumes constant values for each segment’s channel, which is only adequate when dealing with flat roofs, but not when dealing with roofs consisting of planar faces, which is our assumed model, and using the laser scanning data as main information. For the segmentation first and last pulse data and a NDVI (channels 25 and 15 of the HyMap data) are used. Emphasis was on the geometry data (each channel with weight 4), and less on the NDVI data (weight 1). An example of this eCognition segmentation is given in Fig. 6. The gable roofs of all buildings were subdivided into several slight elongated sections in the main roof directions, just approximating the sloped surface by segments with constant heights - independent from the choice of scale parameter. In case of flat roofs the segmentation resulted in reasonable segments.

Instead of the segmentation by eCognition, our segmentation procedure for laser scanning data searches for planar faces. It follows the region growing principle taking the deviation from a plane in 3D into account. Details of the algorithm are first applied in Quint and Landes (1996), enhancements are given in Vögtle and Steinle (2000). Fig. 7 shows the result of the algorithm for the subset based on the last pulse laser scanning data, thus only the geometry is taken into account during segmentation. Parameters were set to include smaller roof extension in the surrounding larger surface patch. The use of geometric data only may lead to problems, when one planar roof surface patch consists of areas with different surface materials.

In order to combine the advantages of both techniques, we applied a strategy consisting of two steps: First we use our segmentation procedure which provides a segmentation based on the geometric laserscanning data. In a second step the segmentation result is introduced into eCognition using the spectral data to split up the initial segments. We used two spectral channels (ch.5 at 493.4 nm wavelength and ch. 120 at 2467.8 nm wavelength) which were also used for classification later on to refine the geometric segmentation. Fig. 8 shows an additional segment on the roof of the building on the lower right, which consists of brick material (cf. Fig. 9), while the rest of the roof is slate material. Because the smooth transition of those patches they could not be separated using the geometric segmentation (cf. Fig. 7). A second spectral segmentation allows the separation of this two patches because of their different spectral properties.

For the classification described in the next section, we used the results of the combined eCognition and IPF segmentation shown in Fig. 8. A comparison with the same classification based on single geometrical IPF segmentation is given in section 5.

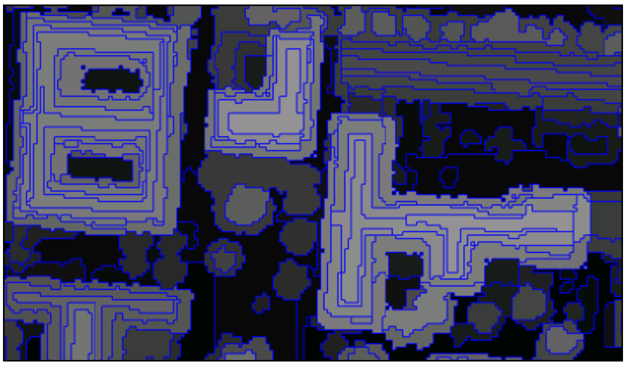


Figure 6: Segmentation (eCognition, scale parameter 50)

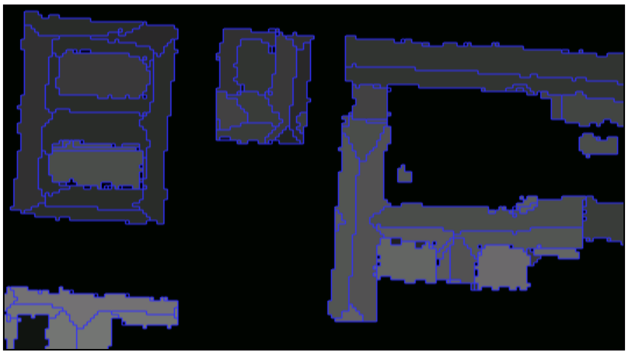


Figure 7: Segmentation (IPF)

Figure 8: Segmentation (IPF and eCognition, scale parameter 30, channels 5, 120)

Figure 9: Aerial image

4.2 Classification

With eCognition software, the combined analysis of multiple datasets of different sensors is possible. The HyMap sensor provides spectral information in 126 channels. Fig. 4 displays example spectra of materials to be classified. A closer look reveals the following:

• Some materials show a significant different spectrum than the others, e.g. aluminum, zinc, brick and copper.

• Some spectra of different surfaces are quite similar, e.g. stone plates and gravel and bitumen.

• Spectra of same material differ significantly due to the surface orientation in relation to the sun angle/illumination, e.g. brick or slate (cf. Lemp and Weidner (2004)).

Furthermore, a number of channels providing geometric information (height, slope, orientation, curvature) are derived from laserscanning data. The main task is to find specific characteristics of the spectra and the geometry to select channels from the hyperspectral and laserscanning data for the classification. From all available channels we actually use a subset of 20 hyperspectral channels and 3 geometric channels, namely height information from first pulse and last pulse data as well as slope information.

For the classification we use the classes shown in Fig. 10, which are ordered hierarchically. This hierarchy mainly reflects the sequence of fuzzy decisions. First, we classify objects and non objects using the height information from laser scanning (first and last pulse). In a second step we derive a set of candidate roofs to be classified, by removing vegetation areas from the objects applying an NDVI (channel 25 and 15 of the HyMap-data) and smaller segments based on their size and their neighbourhood relations to segments of the classes non object and vegetation. Thus, this classification procedure may in principal also be applied, if only a nDSM from first pulse data or derived from other sensor data is available. The roof segments are now classified according to their material and geometry at once. For this purpose, we first have to define membership functions for each class and feature to be used, starting with those material classes with the most significant spectral differences to other materials. The spectral curves shown in (Fig. 4) are resulting not from field spectrometer but directly from the HyMap dataset. Brick shows an increase in the spectrum from the first channels to the last, which seems in our case to be independent from the age of the material. The spectrum of copper has a significant decrease from channel 8 to 20, while aluminum has high reflection values in the first channels and show some characteristic slopes, so we use the channels (1) and (2) and a ratio. Galvanized zinc is decreasing between channel 32 and 40. Slate can be separated from other stonelike surfaces with respect to the slope. So slate surface usually has a significant slope, while gravel and stone plates have to be flat.
As mentioned in section 4, the better part of pollution related to gravel and stoneplate surfaces is caused by a bitumen layer underneath the surface, which is part of almost every flat roof. So we merged the three classes gravel, stone plates and bitumen to one upper class “stonelike/bitumen”.

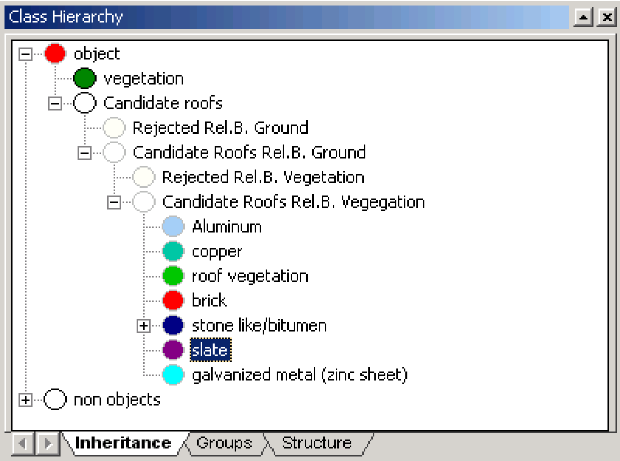


Figure 10: Class hierarchy


Figure 11: Classification based on geometrical segmentation

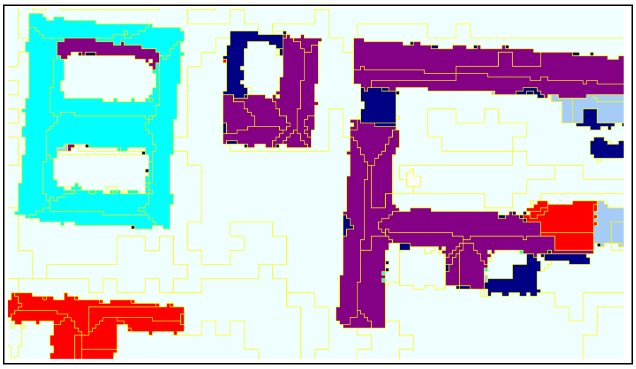


Figure 12: Classification based on combined geometrical and spectral segmentation

A closer look to Fig. 11 and Fig. 12 shows the influences of a refined segmentation technique leading to a more detailed and better classification result. The brick roof segment on the right is correctly detected in Fig. 12 as well as the wrong classified zinc part on the right in Fig. 11 is also eliminated in Fig. 12.

5. RESULTS

In this section we will present and discuss the results of the above segmentation and classification. For the central campus area (white line in Fig. 2) reference data exists, namely a 3D dataset of buildings generated from aerial images with visually approved information about their roof materials from the images and from field check. Fig. 13 displays the result of roof surface classification based on the combined geometrical and spectral segmentation. The membership values of all classes are computed using the fuzzy and(min), which means that all membership conditions must be complied. Fig. 14 indicates a lower stability in smaller segments, which is caused by the limited 4m geometrical resolution of the HyMap data. Also the class “stone like/bitumen” shows a much higher stability than we could reach using the subclasses gravel, stone and bitumen (cf. Lemp and Weidner (2004)).

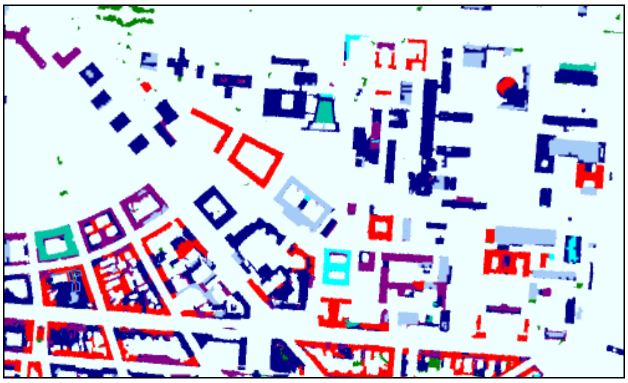


Figure 13: Classification (AND, combined segmentation)

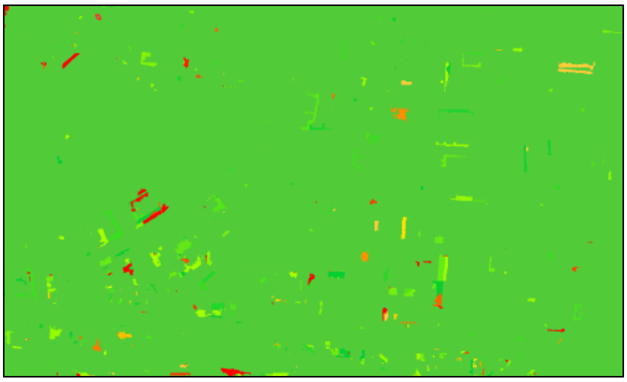
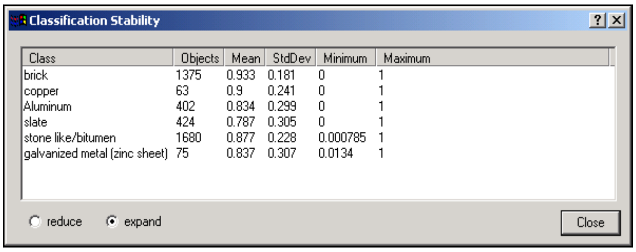


Figure 14: Stability (AND, combined segmentation)


Classification Stability

Class	Objects	Mean	StdDev	Minimum	Maximum
brick	1375	0.933	0.181	0	1
copper	63	0.9	0.241	0	1
Aluminum	402	0.834	0.299	0	1
slate	424	0.787	0.305	0	1
stone like/bitumen	1680	0.877	0.228	0.000785	1
galvanized metal (zinc sheet)	75	0.837	0.307	0.0134	1

reduce expand Close

Figure 15: Stability statistics (AND, combined segmentation)

Most of the roof segments with unstable result – i.e. second best classification result has only small difference in its membership value compared to the best – belong to the above mentioned classes. These segments are shown in red. In case the fuzzy or(max) is used, already one feature with high membership value is sufficient for classification. Usually this strategy leads to a more unstable classification than the fuzzy and(min). Fig. 15 shows the minimum, maximum and mean results for the membership functions for our fuzzy and(min) classification. Slate has the lowest mean membership value of 0.787, which corresponds to the confusion matrix (cf. Table 2). In the following we will discuss the implications on the accuracy of the classification results. In order to compare the eCognition classification with reference values, we exported the resulting classes as a tagged image file (tif), which is readable and analyzable by a GIS software. The attributes of both datasets –

eCognition and reference data – were joined after vectorization. Using multiple sql queries, correct and incorrect results can be detected and visualized as shown in Fig. 16.

Figure 16: Comparison of fuzzy AND(min) classification and reference 3D campus model

The green segments in are representing the correct classified ones with a total of ~71% of the total area of roof surfaces. The yellow patches symbolize correct classified metal roofs (~20% of the total area). Incorrect classified surfaces (red) are accumulating to 4.6% of total area, most of them in small segments with size < 10 m². Zinc and aluminum surfaces are grouped to “metal surfaces”, because they are separated in the eCognition classification, but not in the reference data. The following confusion matrix shows the comparison results in detail.

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 2: confusion matrix of classified areas (in square meters)
(*) Aluminum and Zinc is not seperated yet in reference data

The total amount of 73659 m² classified roof surfaces is correctly recognized in an area of 67167 m² and 91.2% respectively.

6. CONCLUSIONS

In this contribution we presented our improvements for the characterization of urban surfaces, focussing on geometrical and spectral properties of roof surfaces. The main problems with respect to the classification, namely the variability of the materials on one hand and the similarity of some materials' spectra on the other hand are taken into account by our segment based approach. A classification based only on the hyperspectral data is difficult, although the data provides high spectral resolution. The detailed information resulting from laserscanner data with its high spatial resolution combined with the high spectral resolution of HyMap data leads to a hierarchical classification, which delivered reasonable results.

As the reference is a 3D data set generated from aerial images, it could also be used for accuracy assessment of the slope, which is calculated from laserscanning data in our approach, in a next step. For the classification, the accuracy of the slope was less important than the question whether the roof is sloped or not. However, the knowledge of an exact slope will be important for the calculation of the surface area to determine the amount of rainwater collected by any roof segment. Our next topic will be the extension of the classification to the inner city part of Karlsruhe. This regional extension might lead to the necessity of a refinement of the membership functions as well as completely new classes might occur there. Up to now, the analysed six classes appearing in the campus area are a quite limited number, which is probably one reason for the very high accuracy of the classification results. Our work is closely related to the ongoing research on the chemical processes on roof surfaces, because those processes make the basic requirements for our classification. The complex knowledge of the amount of rainwater, the amount of pollution and the direction of the discharge combined with the knowledge of urbanism aspects may lead to economical and ecological important improvements in rainwater discharge and capacity of sewage plants.

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