Segment-Based Characterization of Roof Surfaces Using Hyperspectral and Laser Scanning Data

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***Abstract*— Using remote sensing for urban applications makes high demands on the resolution of the used data - not only concerning its geometric resolution, in terms of ground sampling distance, but also concerning the spectral resolution, in terms of the number of narrow bands, allowing an almost continuous representation of the spectrum. In order to deal with the variability and number of different surface materials with sometimes quite similiar spectral properties, hyperspectral data with its high spectral resolution seems to be mandatory for applications depending on classification of urban surface materials. A recent project of the Chair of Water Chemistry, Engler-Bunte-Institute (EBI), and the Institute of Photogrammetry and Remote Sensing (IPF) – both University of Karlsruhe – aims at the quantitative assessment of pollutants on urban surfaces by chemical analysis and image processing methods. Our research focus at IPF is the characterization of roof surfaces by combined use of hyperspectral and laser scanning data using a segment-based approach. The laser scanning data is primarily used for geometric characterization of the roof patches, but also in combination with the hyperspectral data for material classification. The hyperspectral data already gives rich information about the material, nevertheless the geometry of the roof surface restricts the possible material classes and therefore eases discrimination of materials with almost similar spectra.**

I. Introduction

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 the assessment of the influence of human activity on the status of surface waters and groundwater. Thus, the aim of our research project is not only to derive information on the amount of sealed surfaces in an urban area, but to derive a detailed surface material map. The necessary classes for our application are identified based on chemical measurements on reference roof surfaces, observing that different roof constructions/materials may have similar polluting behaviour. This allows merging of classes with respect to the resulting pollution, although they may have different spectral properties. One example are those material combinations including a bitumen layer and a covering layer from stone materials. The pure material-spectra-oriented classification (cf. [1]) is in our approach supported by geometric clues of surface patches, thus combining geometric data from laser scanning and hyperspectral data for the characterization of roof segments. In the following, we give a short overview on related work. Section III introduces the input data. Our approach for the characterization of roof surfaces in urban areas is presented in Section IV. Recent results as well as a quantitative evaluation follow in Section V, finalized by the conclusions.

II. Related Work

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 permits to incorporate geometric and spectral clues. For classification, we use eCognition, which allows a hierarchical classification and introduction of knowledge by using the different information sources for different decisions within a fuzzy classification scheme.

III. Data

Our approach is based on two different data types: a DSM and hyperspectral data. The available DSM was acquired in March, 2002, with the TopoSys system using the first and the

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last pulse modes. For ease of use within different software packages, $1\ m \times 1\ m$ raster data sets were generated. These data sets differ not only concerning the included objects, but also show systematic deviations. For further discussion on this topic refer to [2] and [9]. The hyperspectral data was acquired in July, 2003, with the HyMap sensor during the HyEurope campaign organized by the DLR (German Aerospace Center). The data was preprocessed (atmospheric corrections, geocoding) by the DLR, Oberpfaffenhofen, using the DSM. The original data has a ground resolution of $4\ m \times 4\ m$. In order to use the data in combination with the DSM, the data was resampled to $1\ m \times 1$ m using nearest-neighbour interpolation. The classification results are compared with a 3D campus model including surface materials as reference data. This model was generated from aerial images taken in spring 2002 and completed by field checks.

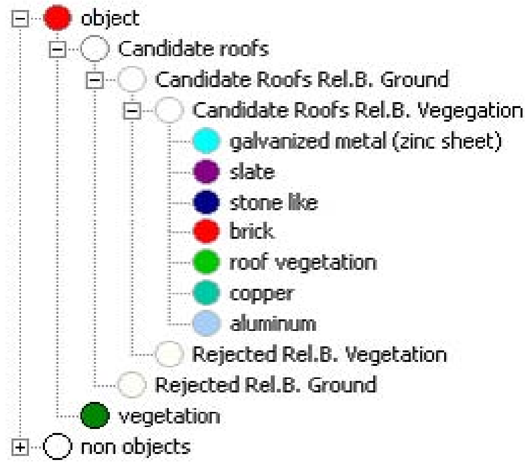

Fig. 1. Class hierarchy

IV. Approach for Data Analysis

The characterization of roof surfaces is based on the analysis of laser scanning and hyperspectral data as already depicted in [9]. 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. The fact that we are focussing on the balance of contained pollutants eases in some cases the requirements on the classification, e.g. a number of flat roof types consist of a bitumen sealing with a variable upper layer of different stonelike materials. In such cases the bitumen layer seems to have the main influence on pollution, while the stone cover is of minor importance. Therefore, a separation in different classes is not nessessary for our application and these categories are joined to one class *stonelike/bitumen*. Furthermore, the geometry of roof patches, namely the slope, is related to the applicable material - at least qualitatively. Thus, the slope information is used as additional clue for classification of the spectrally similar classes *slate* and *stonelike/bitumen*. Our data analysis is structured in two main parts: (1) the geometrical segmentation using an algorithm developed at IPF followed by a second segmentation step by eCognition including spectral information and (2) the classification using eCognition. The quality of segmentation is crucial as it impacts directly the classification result. In the following, we describe segmentation and classification in detail considering a subset of the data as example.

A. Segmentation

The segmentation procedure within eCognition combines spectral and shape information using a region growing approach. The underlying model assumes constant values for each segment's channel, which is only adequate when dealing with flat (horizontal) roofs, but not when dealing with roofs consisting of planar (horizontal and inclined) faces, which is our assumed model, and using the laser scanning data as main information. For gable roofs the segmentation leads to slight elongated segments along the main roof directions, just approximating the sloped surface by segments with constant heights - independent from the choice of scale parameter. We therefore use a two step approach. First, we apply our segmentation procedure for laser scanning data which searches for planar faces by region growing. Details of the algorithm are given in [10] and the application for laser scanning data is already described in [11]. Parameters are set to include smaller roof extensions in the surrounding larger surface patch. The use of geometric data only may lead to problems, in case a planar roof surface patch consists of subareas of different materials. In a second step the first segmentation result is introduced into eCognition using the spectral data to split up the initial segments in order to take care of material changes. 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. Figures 2 and 3 contrast the results of these two steps, showing already the classification results. The used colours correspond to those given in Fig. 1.

B. Classification

A closer look to the spectra of different materials derived from the hyperspectral data reveals the following: (1) Some materials show significant differences in their spectra, e.g. brick and copper. (2) Some materials' spectra are quite similar, e.g. stone plates and gravel. (3) Spectra of same material differ significantly due to the surface orientation in relation to the sun angle/illumination, e.g. brick or slate (cf. [4]). The main task is to identify specific characteristics of the spectra and the geometry to select an appropriate set of channels for classification. Besides the spectral channels, channels providing geometric information may be derived from laserscanning data. We actually use 20 hyperspectral channels manually selected based on the spectra of the surface materials and 3 geometric channels, namely height information from first and last pulse data as well as slope information.

Fig. 1 shows the used classes. Their hierarchy mainly reflects the sequence of fuzzy decisions. First, we classify *objects* and *non-objects* using the height information from laser

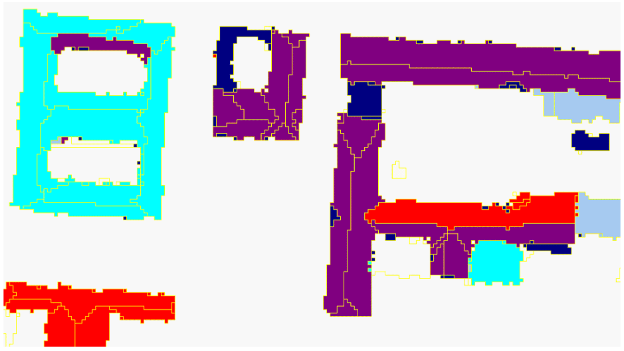

Fig. 2. 1st segmentation step and classification

Fig. 3. 2nd segmentation step and classification

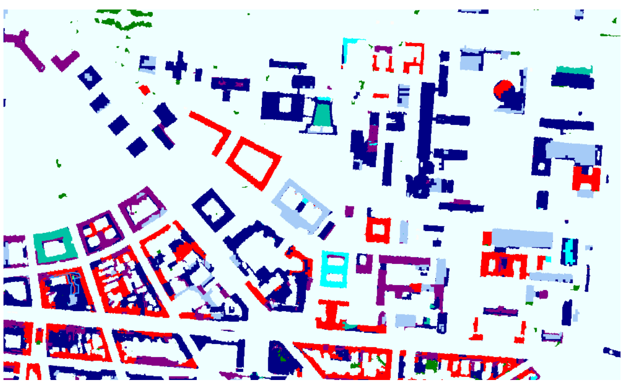

Fig. 4. Classification

Fig. 5. Stability

Fig. 6. Comparison to reference data

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 normalized DSM from first pulse data or derived from other sensor data is available. The roof segments are then classified according to their material and geometry. For this purpose, we 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. 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 values in the first channels and show some characteristic slopes, so we use the channels 1 and 2 and a channel ratio. Galvanized zinc is decreasing between channel 32 and 40. Slate can be separated from other stonelike surfaces with respect to the slope: slate surfaces usually have a significant slope, while surfaces of gravel and stone plates are flat. As mentioned above the better part of pollution related to gravel and stone plate surfaces is caused by a bitumen layer. Therefore, the three classes *gravel*, *stone plate* and *bitumen* are fused to one main class *stonelike/bitumen*. A closer look to the classification results indicate the impact of the adapted segmentation technique, leading to a more detailed and better classification result.

V. Results

In this section we present and discuss the results for the central campus area with existing reference data. Fig. 4 displays the result of roof surface classification based on the combined geometrical and spectral segmentation, again using the colour coding given in Fig. 1. The membership values of all classes are computed using the *fuzzy and(min)*, which means that all membership conditions must be complied. Fig. 5 indicates a lower stability measure for smaller segments using the traffic light coding. The stability measure is derived by eCognition based on the differences of membership values.

TABLE I
CONFUSION MATRIX

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%	

This problem for smaller segments is caused by the limited geometrical resolution of the HyMap data. The class *stone like/bitumen* shows a much higher stability than we could obtain using the subclasses *gravel*, *stone plates* and *bitumen* as in [9].

Fig. 6 displays the comparison between classification and reference. The green segments represent 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 approx. 8%. These include also roof surfaces for which the assigment of the reference – zinc or aluminium – is uncertain, because even by field checks, visual discrimination is sometimes impossible. The area with uncertain reference is about 3.4% of the total area, thus leaving 4.6% of total area as truely incorrect classified segments, most of them small with sizes $< 10\ m^2$. Zinc and aluminum surfaces are grouped to *metal surfaces*, because they are separated in the eCognition classification, but not in the reference data, due to the problems described above. The total amount of 73659 m classified roof surfaces is correctly recognized in an area of 67167 m and 91.2% respectively (cf. confusion matrix in Tab. I).

VI. CONCLUSIONS

In this contribution we presented our approach for the characterization of roof surfaces for the assesment of pollutants in rain runoffs from roofs. 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 a segment-based approach. A classification using hyperspectral data only is difficult, although the data provides high spectral resolution. Geometric features derived from high resolution laserscanning data are not only essential for the desription of roof segments, but prove to be useful for the classification. The result for the classification are evaluated using a 3D campus model including information about roof surface materials. As the 3D reference data is generated from aerial images, it could also be used for accuracy assessment of the geometric properties of the roof surfaces – such as slope or area calculated from laserscanning data – 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, on which pollutants are accumulated during the time between rainfalls. Our next aim will be the extension of the classification to the part of the city centre of Karlsruhe. This regional extension will show, if our approach is applicape for more complex areas as the campus area, which includes large buildings. Thus, the variability in the city center will be higher. Furthermore, completely new classes might occur. Up to now, the analysed 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.

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