Automated Differentiation of Urban Surfaces Based on Airborne Hyperspectral Imagery

Sigrid Roessner, Karl Segl, Uta Heiden, and Hermann Kaufmann

Abstract—The urban environment is characterized by an intense use of the available space, where the preservation of open green spaces is of special ecological importance. Because of dynamic urban development and high mapping costs, municipal authorities are interested in effective methods for mapping urban surface cover types that can be used for evaluating ecological conditions in urban structures and supporting updates of biotope mapping. Against this background, airborne hyperspectral remote sensing data of the DAIS 7915 instrument have been analyzed for their potential in automated area-wide differentiation of ecologically meaningful urban surface cover types for a study area in the city of Dresden, Germany. The small urban structures and the high spectral information content of the hyperspectral image data require the development of special methods capable of dealing with the resulting large number of mixed pixels. In this paper, a new approach is presented that combines advantages of classification with linear spectral unmixing. Since standard unmixing techniques are not suitable for an area-wide analysis of urban surfaces representing a large number of spectrally similar endmembers (EMs), the mathematical model, were extended and a new method for pixel-oriented EM selection was developed. This method reduces the number of possible EM combination for each pixel by introducing spectrally pure seedlings and a list of possible EM combinations into a neighborhood-oriented iterative unmixing procedure. The results and their comparison with standard spectral classification methods show that the new pixel- and context-based approach enables reasonable material-oriented differentiation of urban surfaces.

Index Terms—Classification, endmember selection, spectral unmixing and urban environment.

I. INTRODUCTION

URBAN areas are mostly dominated by various types of artificial materials. Under these conditions, preservation and higher evaluation of remaining green spaces is one of the main tasks in ecological urban planning. For the large cities of Germany, detailed area-wide mapping of urban biotopes has been carried out during the last 20 years based on visual interpretation of CIR (Color Infrared) aerial photographs and field investigations [1], [2]. This approach results in a detailed assessment of biotopes. However, the high pace of city development and limited financial means of the municipal authorities make the analog mapping approach too time consuming and expensive for regular updates. Against this background, the presented study investigates the potential of airborne hyperspectral image data for a spectrally-based differentiation of urban surfaces into ecologically meaningful categories. The goal is to develop an automated approach which is capable of dealing with the high variability of urban surfaces and the resulting spectral mixing effects in the image data.

A wide range of studies have already dealt with opportunities for automated image analysis in the urban environment. For many years, panchromatic aerial photographs have been the main source of remote sensing data for detailed inventories of urban areas. These investigations have been focusing on the development of automated methods for geometric three-dimensional (3-D) assessment of man-made objects, mainly buildings and streets [3]. With an increased influence of ecological aspects in urban planning, methods for area-wide urban biotope mapping have been developed [2]. Due to the variety and complexity of the mapped categories (see Section III), their assessment has been mostly based on visual interpretation of CIR aerial photographs [1].

Although this analog approach yields a high degree of spatial and thematic detail, alternatives toward an automated assessment of urban surface characteristics have been investigated due to the high costs of visual interpretation. Most of these studies have used multispectral satellite imagery of medium resolution (Landsat5-TM, SPOT-HRV, IRS-LISS) and were based on common image analysis techniques, such as maximum likelihood (ML) classification, NDVI-based classification, or PC analysis [4]–[7]. Other studies have incorporated additional contextual information to improve the results of per-pixel classifications [8]–[10]. Due to the limited spatial and spectral resolution of these data, only fairly broad categories such as urban developments of different density and main roads could be distinguished.

The problems of limited spatial resolution of the image data have been overcome with the wider availability of airborne multispectral scanners (TMS, DAEDALUS-ATM), which recently have been complemented by high resolution satellite-based systems (IKONOS). Studies using the TMS [11] and the DAEDALUS-ATM scanner [12], [13] have shown the advantages of improved spatial resolution and the suitability of this data for urban applications. However, limits of spectral differentiation of material properties of nonvegetated surfaces remained. In this connection, hyperspectral image data (AVIRIS, DAIS, HYMAP) have been opening up new opportunities for surface differentiation based on spectral characteristics including the possibility for quantitative assessment.
of bio- and geochemical parameters. This has been widely demonstrated by studies in the fields of vegetation [14], [15] and geology [16]–[18]. So far, however, only a small number of studies has investigated the potential of hyperspectral image data for characterization of urban surfaces. Most of these studies have dealt with selected surface categories and phenomena [19]–[21].

II. STUDY AREA, DATA, AND PREPROCESSING OF HYPERSONTAL IMAGERY

The study area is situated in the city of Dresden which is one of the largest cities in Germany. The test site covers a northsouth transect of 7 km x 3 km [Fig. 4(g)] containing a variety of urban structures including densely developed areas of the inner city in the north, large vegetated areas (park) in the center, and suburban areas in the south.

Hyperspectral image data were recorded on July 23, 1997, between 11:23 and 11:28 local summer time by the 79-channel digital airborne imaging spectrometer (DAIS) 7915 reaching from the visible to the thermal infrared wavelength ranges [22]. The flight altitude of 3500 m results in a pixel size of about 7 m. Table I shows the characteristics of the DAIS 7915 instrument for the 72 reflective bands which were used in this study. Preprocessing of the DAIS 7915 data, including system corrections and radiometric calibration, was carried out by the DLR [22]. Since the data showed random and systematic noise content for the bands of the SWIR I and SWIR II detectors, a maximum noise fraction transform (MNF) [23] was applied to the bands of these spectrometers and selected MNF components were Fourier-filtered. Preprocessing also contained conversion of radiance to reflectance data using empirical line calibration [24] based on field spectrometer measurements. For image rectification, a semi-parametric approach was developed which includes the parametric model of the roll angle, line features as ground control information and bilinear resampling.

III. OBJECTIVES OF HYPERSONTAL IMAGE ANALYSIS IN THE URBAN ENVIRONMENT

The goal of this study is the development of an automated method for hyperspectral image analysis that is capable of exploiting the full spectral and spatial information content of the data to differentiate urban surface cover types. Thematic categories of interest are determined by the principles of urban biotope mapping, which primarily distinguish main types of urban land use such as nonindustrial development, industry and business, transportation, green spaces of intense maintenance, wetlands, forests, or water. For further differentiation of developed areas, their functional use is playing a major role, whereas natural vegetation is mapped according to leading plant communities and geobotanical factors. Additionally, for all developed areas, the degree of surface sealing against infiltration of runoff water is estimated.

For the purpose of an automated material-oriented differentiation of urban surfaces a hierarchical structure of categories has been developed (Fig. 1). On the first level (level I), urban surfaces are subdivided into artificially sealed and nonsealed areas. Sealed surfaces are further distinguished into buildings and open areas (level II), since buildings determine the ecological conditions of their surroundings. Within open spaces of artificial coverage roads and railways (areas of traffic) form a separate category in level III, because they always represent boundaries between biotopes. The category of nonsealed surfaces (level I) contains all areas which are occupied by natural surfaces. They are subdivided into the main categories of vegetated and nonvegetated areas (level II). On the third level (III), vegetated areas are further differentiated into grassy (meadow/lawn) and tree-/bush-type vegetation. Non-vegetated areas are subdivided into water and bare soil (Fig. 1). The categories of level III represent the thematic frame for an area-wide assessment of urban surfaces according to their material properties which is discussed in more detail in Section V-A.

IV. ITERATIVE LINEAR SPECTRAL UNMIXING APPROACH BASED ON PIXEL-ORIENTED ENDMEMBER SELECTION

Airborne hyperspectral imaging of small urban structures results in high spatial and spectral detail. However, spectrally mixed pixels represent the dominating pixel type, since the recorded radiation is an integrated sum of radiances of all types of surfaces within the instantaneous field of view (IFOV) of the sensor. These mixing effects cause problems for classification approaches that require spectral templates for all spectrally distinct surfaces and their mixtures occurring in the image data. In contrast, the spectral unmixing approach requires less a priori
information, because the spectrum of a pixel is modeled by the mixture of different endmember (EM) spectra. Although, linear spectral unmixing seems to be the more suitable approach for hyperspectral data analysis, its successful application in the urban environment requires special techniques for EM selection. The following sections describe our new approach (Fig. 2) which combines advantages of spectral classification with linear spectral unmixing and includes a pixel-oriented EM selection procedure.

A. Theoretical Background of Linear Spectral Unmixing

Linear mixture models allow estimation of the abundance of each EM (class) within a pixel. Linear spectral unmixing approaches can be subdivided into full unmixing ones and partial unmixing ones [25]. Full unmixing models require spectral knowledge of all possible EMs which can occur in a pixel. Partial unmixing models such as constrained energy minimization (CEM) [26] and orthogonal subspace projection (OSP) [27] can deal with unknown EMs. The developed approach is based on full unmixing, because in the urban environment spectral information can be acquired for all possible EMs. A commonly used technique is the constrained least-squares method [28]. If the single image bands are convolved by different noise levels, linear spectral unmixing is extended by an additional stochastic model describing the noise characteristics of the image bands in form of a covariance matrix $C_{\text{noise}}$. For this purpose, the linear Gauss–Markov Model [29] is used, which is also known as the weighted least-squares method [28]. In our approach, this model is extended including the covariance matrices of the EMs, which results in the Gauss–Helmert Model [30]. Thus, EMs represent fixed and random variables at the same time. This model allows weighting of spectral information for pixels and EMs leading to a more realistic description of the spectral variability of natural surface cover types. The goodness of the obtained abundances is checked by a hypothesis test (5% error probability). A more detailed discussion of these techniques can be found in [31].

B. List-Based Endmember Selection

The quality of EM selection is crucial for the success of spectral unmixing. This problem can be illustrated using the geometrical model of linear spectral unmixing. In this model pixels represent points in the $n$-dimensional feature space, where $n$ is the number of bands. Assuming the two-dimensional case with only three EMs mixing, the mixed pixels fall inside a triangle defined by these EMs. Pixels outside of this triangle cannot be unmixed in a meaningful way since combinations of positive and negative abundances occur. Thus, spectral extrema represent good EM estimates which lead to positive abundances for the majority of the image pixels. Under these conditions, unsupervised techniques are often used for EM selection since they identify spectra with extreme shapes based on transformed image data as a result of PCA, MNF, MAF or convex geometry concepts [32]–[34]. However, these unsupervised techniques do not necessarily result in EMs which represent thematically meaningful categories. Supervised definition of EMs increases thematic control. At the same time, this approach may lead to EMs which do not represent spectral extrema. Unmixing consequently results in positive and negative abundances. Additionally, for successful unmixing EM spectra have to be characterized by spectral features which are distinct from each other. These described constraints of standard linear spectral unmixing do not meet the conditions in the urban environment where a wide range of thematically definable EMs is required to perform an area-wide differentiation of urban surface cover types.

Therefore, methods have to be developed which can deal with a high number of EMs and avoid negative abundances. Our approach narrows the number of possible EM combinations for each pixel. All linearly independent EM combinations are determined and stored in a list while each of the combinations consists of a limited number of EMs. This study sets two EMs per combination since it leads to the highest probability for positive abundances. It also takes into account the limited number of spectrally significant surface cover types which can fit in a pixel of size between 3 and 7 m. Additionally, the list concept allows exclusion of combinations which do not make sense or have very little likelihood of occurrence. During the spectral unmixing procedure all combinations of the list are tested and evaluated using a hypothesis test. Finally, the most likely decision passing the test criterion is accepted.
C. Pixel-Oriented Selection of Endmember Combinations and Iterative Unmixing

Despite the advantages of the described list concept, the problem of false classifications still exists due to spectrally similar EM combinations. Even if each combination in the list consists of spectrally distinct EMs, similar EM mixtures can occur and lead to confusion. Therefore, the number of possible EM combinations needs to be further reduced for each pixel. For this purpose an iterative approach for the selection of the most likely EM combination for each pixel was developed (Fig. 2) integrating spectral classification and linear spectral unmixing to increase spatial and thematic control on the unmixing procedure.

This approach starts with the thematic and spectral determination of EMs (urban surface cover types). In the next step, all pixels need to be identified which allow a clear recognition of surface cover types. In our case we define this requirement to be best fulfilled by spectrally pure pixels. They are determined by a supervised ML classification with a very small Mahalanobis-Distance. The resulting seedlings serve as spectral and spatial starting points for the selection of the most likely EM combinations for mixed-pixels occurring in the neighborhood of the spectrally pure pixels.

The iterative unmixing procedure (Fig. 3) starts with the definition and storage of all possible EM combinations in the list. All classified seedlings (A, B, and C) are then determined as potential EMs in a spatially defined neighborhood of nonclassified pixels (1, 2, and 3). For further processing three cases have to be considered. Case 1 represents the ideal situation where different EMs (A and B) exist within the predefined neighborhood. Under these conditions it is very likely that the unknown pixel 1 contains a mixture of the surface cover types represented by the classes A and B. Since it has been previously defined that a mixture consists of two EMs, combination A-B is tested for this pixel during the unmixing process. Case 2 represents the less ideal situation where only one EM can be identified in the form of a seedling in the neighborhood of pixel 2. In this case all combinations containing EM A are selected from the list and tested in the unmixing process. The same procedure is applied in case 1, if none of the checked combinations passes the hypothesis test. This means all combinations containing the classes A and B are tested. However, if no seedling pixels exist in the neighborhood (case 3), this pixel is ignored at the current stage of the unmixing process.

In case 1, additional constraints are applied to enhance spatial control over the unmixing procedure. First, the position of the second EM B is limited to those pixels which spatially enclose the mixed pixel resulting in three possible positions for a $3 \times 3$ neighborhood. Second, if there is only one EM found, the search area is extended to a $5 \times 5$ window before executing case 2. Tests based on larger windows did not improve the results because seedlings of more distant objects are considered in the unmixing leading to spectral confusion.

In case 2, the spatial control is reduced to one seedling in the direct neighborhood of the mixed pixel. Under these conditions problems occur in areas of shadow. The low albedo of these mixed pixels causes unmixing decisions identifying water as the unknown second EM. The result is a false dominance of water. This problem is solved by excluding water as a possible second EM from the list. This means water is only detected if at least one seedling pixel is initially classified as water.

The iterative unmixing procedure leads to spatial growing of the unmixing results around classified pixels (Fig. 3). The classification and unmixing results are combined and form the basis for the next iteration of EM selection and unmixing. In contrast to the initial ML classification, the result of the unmixing procedure consists of two classes which both have to be considered during further EM selections (pixel 3). This iterative procedure is repeated until no more pixels are left which can be unmixed under the condition of fulfilling the hypothesis test.

V. APPLICATION OF APPROACH TO STUDY AREA AND RESULTS

Based on the developed approach, an area-wide differentiation of urban surface cover types was obtained for the whole study area [Fig. 4(g), (h)]. In this section the application-specific parameterization of the different steps is described and the results are validated in comparison with the results of standard classification methods.

A. Determination of Endmembers and Seedling Identification

The thematic framework for determination of training and EM information is represented by the urban surface cover types of level III in Fig. 1. Thematic and spectral variability within these types was investigated using measurements with a field spectrometer (Field FR of Analytical Spectral Devices), anal-
Fig. 4. Results of different steps of the combined classification and iterative unmixing approach and comparison with standard classification methods.

Analysis of the hyperspectral image data, CIR aerial photographs and 1:5000 land register maps. The assessment of spectral training information was based on the hyperspectral image data and led to several categories and additional spectral variations for each
B. Iterative Unmixing and Results

The identified seedlings are the starting point for iterative linear spectral unmixing. For the unmixing procedure every second DAIS band covering the reflective part of the spectrum was selected, since these bands represent the shape of the spectra in an optimal way. In contrast to the ML classification, spectral shape information are used by the unmixing model. For the iterative approach a list containing 555 EM combinations was defined. The unmixing procedure stopped after 16 iterations when 100% of the study area was unmixed. The final result for the dominating surface cover type is shown in Fig. 4(d) (subset) and Fig. 4(h) (whole study area). Fig. 4(c) contains the abundances for the dominating EM within the pixel. Visual inspection of the results shows that sensible EM combinations could be identified for the majority of pixels which were rejected in the process of the ML classification. The result for the whole study area allows identification of typical urban structures formed by characteristic combinations of the classified urban surface cover types.

To evaluate our approach, accuracy assessment was performed analyzing confusion matrices of representative control pixels. These pixels were determined within the subset shown in Fig. 4(a) using CIR aerial images and field mapping. The categories of interest correspond to the surface cover types in Table II. The percentage of control pixels which were correctly identified by the pixel-oriented iterative unmixing approach (PIU) is listed in Table III. For methodological validation the subset was also analyzed using standard linear spectral unmixing [Fig. 4(e)] and ML classification [Fig. 4(f)]. Accuracy assessment for these methods was performed in the same way and the results are also included in Table III.

Iterative unmixing [Fig. 4(d)] is characterized by an overall good accuracy (>80%) for all surface cover types. In comparison to the other methods a balanced result was achieved for all classes reflecting the advantages of combining classification and unmixing techniques. However, problems of misclassification occur between buildings and neighboring streets which are caused by spectral similarities between materials covering these surfaces and the influence of shadow. Therefore, methods have to be developed which allow an improved separation of buildings from surrounding open spaces.

List-based linear spectral unmixing [Fig. 4(e)] was performed using the constrained least square method while testing all EM combinations of the list for each pixel. This method represents the spectral unmixing component of our approach excluding spatial control. Identification of mixed pixels shows a tendency of quasi-random combinations of EMs, especially for spectrally similar EMs such as roofs, areas of traffic and open spaces.

Since there is no spatial control of the unmixing procedure, the high number of simultaneously used EMs increases the likelihood for confusion. This is especially obvious in the case of roofs (only 45.9% correctly identified). Another problem is the
false identification of water in areas of shadow. The reasons have already been discussed in Section IV-C.

The ML classification [Fig. 4(f)] produces good results for larger areas covered by spectrally distinct and homogeneous surfaces (e.g., lawn, meadow and large roofs). Problems occur in areas of small structures leading to mixed pixels (areas of traffic 44.5%). These areas show a false dominance of roofing materials. The mixed pixel situation also results in seams of misclassified pixels following the borders between different surface cover types. These problem are caused by the high spectral variability of mixed pixels which can not be assessed by equivalent training information.

VI. CONCLUSIONS AND OUTLOOK

The results show that spatial control is the most important component of the developed iterative unmixing approach which is independent from a specific unmixing model allowing the implementation of new models (e.g., nonlinear ones) in the future. The results show a reasonable area-wide differentiation of urban surfaces. Improvements are especially strong in areas dominated by mixed pixels which cover 74% of the study area. The obtained results are a good basis for further ecological evaluation of urban structures since they allow quantitative assessment of the areal coverage of different surface cover types. The results can also be used for an area-wide detection of changes in relation to previous classifications or existing biotope mapping. This shows the great potential of hyperspectral image data for detailed inventories of urban surface cover types. However, successful area-wide analysis of such highly heterogeneous surfaces requires special approaches which allow exploitation of the full spectral and spatial information content of the hyperspectral data.

The results obtained at the present stage of methodological development show the great importance of good initial classification of seedlings. Limitations occur mainly due to the rather large pixel size (about 7 m) of the DAIS data. This leads to problems especially in areas of small structures such as suburban neighborhoods with single houses. Insufficient spatial resolution also decreases the spatial accuracy of the results because of complex mixing situations. During future work the influence of pixel size on the quality of the unmixing result will be studied using hyperspectral DAIS and HYMAP data of higher spatial resolution (about 3 m). Another problem in seedling identification is the confusion between buildings and neighboring open spaces covered by similar artificial materials. Since buildings are characterized by distinct shapes, future work will focus on extraction of shape-based features from the hyperspectral image data to incorporate this information in seedling detection. However, the results which have been obtained so far prove the suitability of our approach for a detailed, area-wide differentiation of urban surfaces into ecologically meaningful categories. Future experiments are expected to assess the full potential of this method for analysis of the urban environment.

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Sigrid Roessner received the Ph.D. degree from the Faculty of Engineering, University of Karlsruhe, Karlsruhe, Germany, in 1996. She is currently a Research Scientist with the Geo-ForschungsZentrum, Potsdam, Germany, in the Remote Sensing Section of the Division Kinematics and Dynamics of the Earth. Her research interests are in applied remote sensing and GIS in the fields of urban ecology, physical geography, and natural hazards.

Karl Segl received the Ph.D. degree from the Faculty of Engineering, University of Karlsruhe, Karlsruhe, Germany, in 1996. He is currently a research scientist at the Geo-ForschungsZentrum, Potsdam, Germany, in the Remote Sensing Section of the Division Kinematics and Dynamics of the Earth. His research interests focus on new methodological developments for hyperspectral data analysis, pattern recognition, image correction and sensor design.

Uta Heiden received the degree in geocology from the University of Potsdam, Potsdam, Germany, in 1999. She is currently pursuing the Ph.D. degree at the Geo-ForschungsZentrum, Potsdam, in the field of hyperspectral data analysis in the urban environment.

Hermann Kaufmann received the Ph.D. degree in geology and remote sensing from the Ludwig-Maximilians University of Munich, Munich, Germany. He is currently Head of the Remote Sensing Section, Geo-ForschungsZentrum, Potsdam, Germany, and holds a Chair at the University of Potsdam. In 1992, he received the inauguration in remote sensing from the Faculty of Engineering, University of Karlsruhe, Karlsruhe, Germany. In his 20 years of experience, he has been Principal Investigator of a large number of national and international projects funded by various governmental and industrial institutions. Present research is primarily focusing on the processing and evaluation of hyperspectral laboratory, field, and airborne data and the design of spaceborne imaging spectrometers.