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DETERMINATION AND VERIFICATION OF ROBUST SPECTRAL FEATURES FOR AN AUTOMATED CLASSIFICATION OF SEALED URBAN SURFACES

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ABSTRACT

Urban surface materials have an immense influence on ecological conditions of urban areas. In this context, frequent material-oriented identification of urban surfaces can support municipal authorities in planning processes. This requires hyperspectral remote sensing data that are characterized by a high spectral and spatial resolution. For full exploitation of the information content detailed spectral knowledge of urban surfaces is required and automated methods are needed for effective processing of those data. In this study, a methodology for the determination and validation of materials-specific spectral features has been developed that can be used for automated identification of urban surface materials. It is demonstrated for representative urban surfaces in the cities of Dresden and Potsdam, Germany. First, an urban spectral library consisting of field and image spectra was developed that has been analyzed in regard to typical spectral features and their variations. Based on a visual analysis, robust features that are highly independent on spectral variations caused by e.g. illumination and degradation have been selected. The quality of these features has been validated in regard to an improved separability of urban surface materials analyzing a confusion matrix within a classification process. For this purpose, the features were described numerically using adapted feature functions. The results of the classification show a very good separability especially for predominantly bright urban surfaces, but also for darker materials with weak reflectance features. Even the differentiation between spectrally similar urban surfaces was feasible. The derived robust spectral features reduce the need for test-site specific training information. This way, the developed methodology represents an important step towards a fully-automated identification of urban surfaces.

INTRODUCTION

Since urban surface materials have a great importance for ecological conditions in cities, one of the main task of municipal authorities is the mapping of urban surfaces. Due to limited financial means, the development of automated methods for an effective surface inventory is needed. Recent studies using hyperspectral remote sensing data show their successful application (i), (ii), (iii). Hyperspectral data are characterized by a high spatial and spectral resolution and thus, enables a material-oriented identification of the urban surface.

The analysis of such data often requires the time-consuming building of a local spectral library. It cover spectral characteristics and variations of the particular test site and will be used e.g. as training data for supervised classification. A more effective way is the use of spectral characteristics for surface identification that are generally applicable for a middle European city. The knowledge of typical spectral features and the nature and effect of their variations are requirements for an efficient hyperspectral data analysis. It enables automated and unsupervised identification of endmembers and thus minimizes the effort for building local spectral libraries.

Therefore, the objective of this paper is the determination and validation of robust spectral features for each surface material. They are identified by comprehensive visual analysis of the spectral characteristics and the type and effect of their spectral variations. The quality of the obtained features is validated in regard to the separability of materials. For this purpose, features are described numerically using a number of feature functions.

METHODOLOGICAL APPROACH

The overall approach of this study is divided in three main parts. First, an urban spectral library was developed and analyzed covering a wide range of typical surface materials for urban areas in middle-European cities. Second, the obtained spectral knowledge was used for the determination of robust spectral features for each surface material. Finally, in the separability analysis the feasibility of the robust features for an automated differentiation of urban surfaces was tested. In the following used methods are described in more detail.

Development of an urban spectral library

For the investigation of spectral characteristics of surface materials, spectral features, such as absorption bands (local reflectance minima), reflectance maxima and albedo are used. Furthermore, three approaches of spectral information acquisition have been applied. First, representative surface materials were measured spectrally in the field. Second, due to the limited accessibility of most of the roof materials in the field, samples were collected and measured separately. Third, image spectra of the same materials have been obtained from the hyperspectral HyMap data and compared to the field measurements in order to analyze spectral variations of urban surfaces.

Spectral reflectance measurements of representative sealed surfaces were recorded in the field in the test sites of Potsdam and Dresden, Germany. Both cities are covered with a wide range of surface materials that are typical for a middle European city. Material information was acquired based on field inspections and aerial photographs. The measurement of roofs in the test sites was not possible for all of the representative materials because of limited accessibility of some roofs. Therefore samples of different roof materials, degradation and coating were collected. They were measured under open sky and direct sun illumination in nadir position.

All spectral measurements were carried out using a field spectrometer (ASD FieldSpec Pro FR). The sensor records data in the wavelength range between 0.35 µm and 2.50 µm in 2151 narrow channels. The reflectance spectra of the surface materials were computed using a Spectralon panel (Halon) as reference. A single spectral measurement has been defined by 50 scans that are averaged by the spectrometer and saved in a single spectrum. The total number of single spectral measurements for one material depends on homogeneity and size of the investigated surface.

For the analysis of spectral variations within the different materials image spectra of the same materials have been obtained from hyperspectral HyMap data of Potsdam and Dresden, Germany (6 m spatial resolution). For comparison of the image spectra with field spectra, the original HyMap radiance data were corrected for solar irradiance and atmospheric effects using the non-parametric empirical line method. Further, hyperspectral HyMap data were georeferenced to the topographic map (1:25.000). The mean positional accuracy amounts to 7.7 m for Dresden and 4.0 m for Potsdam. This enables a correct assignment of field spectra to image spectra.

Based on spectral field investigations respective materials have been identified in the image data and further analyzed for their spectral variations. For each material several areas of interest were identified. For all of these areas the spectral characteristics were obtained separately by averaging several spectrally pure pixels.

Determination of robust features

In this study, a method was developed that allows the determination of robust spectral features and their numerical description for any computer-based analysis. For the extraction of the robust spectral features several functions have been introduced allowing the description of a wide range of different feature types.

Image spectra of the urban spectral library form the basis for the determination of robust spectral features within three processing steps. First, features that are representative for all sample spectra of the respective material are selected by visual analysis. This way, the existing spectral variations are taken into account. Second, the feature selection is further constrained regarding the separability between sealed materials. Third, the obtained robust spectral characteristics are transformed into numerical values using appropriate feature functions. They comprise mean and standard deviation (Stdev), ratio, area function, absorption position and depth, reflection height and position as well as offset, gain and RMS of a regression line. All features are calculated between specific wavelength ranges defined by visual analyses. The used feature functions are illustrated in Figure 1.

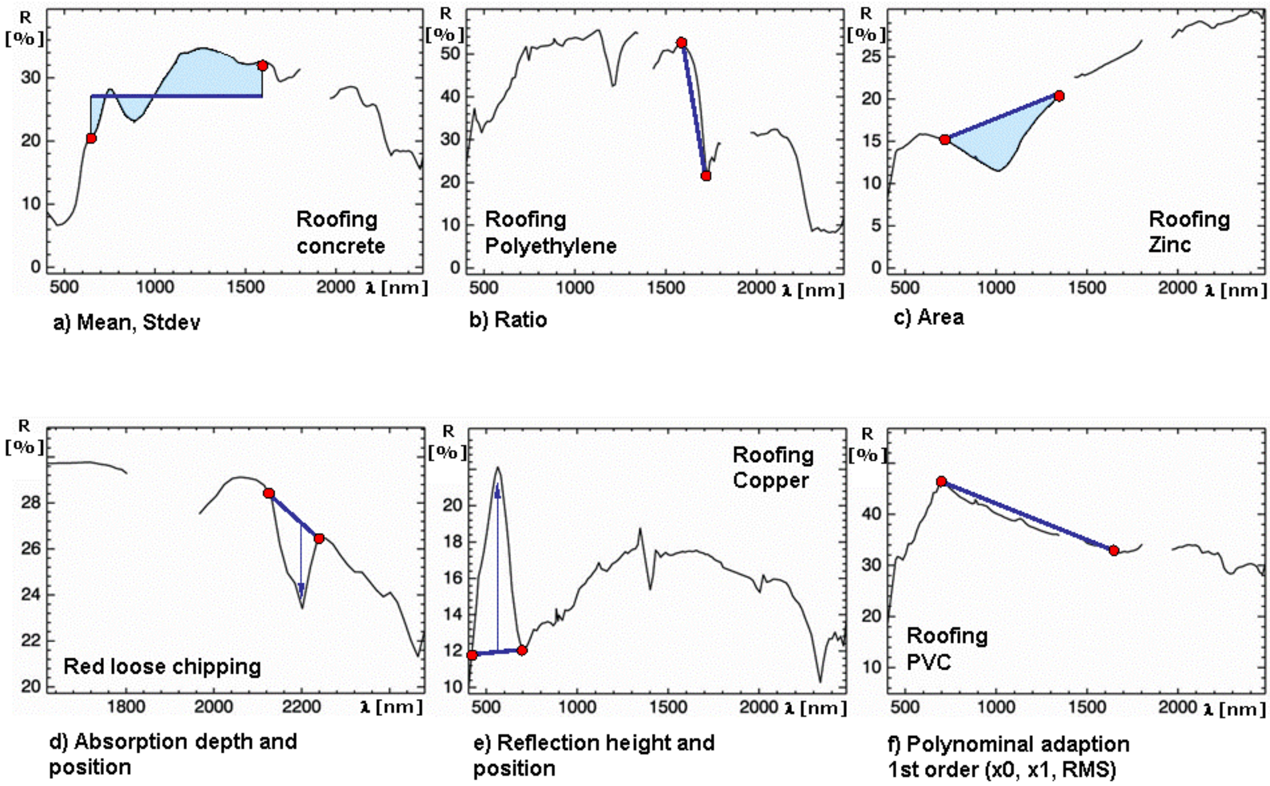

Figure 1: Numerical description of spectral features using feature functions; feature values are calculated between specific wavelength ranges (symbolized with points). The example spectra are obtained from hyperspectral HyMap data.

Materials with a typical brightness and flat curve progression can be differentiated using mean and standard deviation values (Figure 1a). This is of high importance for the discrimination of materials with low spectral reflectance properties such as characteristically for dark materials. The ratio is sensitive to the decrease or increase of reflectance between two wavelength positions (Figure 1b). Broad absorption bands such as shown in the example of Figure 1c can be expressed by the area that is enclosed by the reflectance curve in a specific wavelength range. In case of narrow absorption bands the absorption depth and position are suitable features (Figure 1d). A comparable distinct feature is the reflectance peak described by its wavelength position and height (Figure 1e). Both, absorption and reflection features are derived from the difference between the reflectance curve and the hull function within a defined wavelength range. Another characteristic feature is a constant increase or decrease of reflectance between two wavelength positions. This spectral property can be described by the gain and offset of a regression line and the root mean square error (RMS) of the polynomial fit as a measure for the spectral continuity (Figure 1f).

Validation

The visual selection of the robust features needs to be validated regarding the ability of these features for differentiation between surface materials. For the validation the overlap in the feature space is analyzed. For this purpose, distances such as Bhattacharyya Distance, Transformed Divergence and Jeffreys Matusita Distance are widely used (iv), (v). Confusion matrices calculated by classifiers such as Maximum-Likelihood, Spectral Angle Mapper and Artificial Neural Network can also be used for the quantification of the separability. However, the results of these methods become more and more inaccurate with an increasing number of features.

Due to the high number of features to be considered within the separability analysis, the mentioned distances and classifiers are not suitable. The Parallel-Epiped classifier benefits from an increasing number of features whereas in case of less features its performance is moderate. Therefore, in this study, the Parallel-Epiped classifier is used for the validation of robust spectral features. A material class is defined by the minimum and maximum values for each spectral feature and based on these data the confusion matrix is calculated. For separability analysis the values of commission (percentage of extra pixels per class) are further analyzed.

RESULTS

Spectral characteristics of urban surface materials and their spectral variations

The spectral analysis of the field and laboratory data shows a high number of spectrally different sealed materials with distinctive spectral features. In the result 21 fully and partially sealed urban surfaces were investigated that are representative for middle European cities. They could be further distinguished in mineral/ceramic, synthetic and metallic materials. Examples for mineral/ceramic materials are roofing tiles, roofing concrete and roofing gravel as well as concrete of sealed open spaces and cobblestone pavement. Representatives of the synthetic material group are roofing bitumen, roofing polyvinyl chloride, asphalt and dark loose chippings. The metallic group contains particularly roof materials such as zinc, copper and aluminum. In Figure 2 the spectral field measurements of selective roof materials are shown.

Tiles are often used materials for roofs in residential areas. They predominantly consist of ferric oxides, quartz and clay minerals. Further they are covered with clay sludge for conservation purposes and for coloring. The spectrum in Figure 2 show absorption features of iron bearing minerals (e.g. Fe_2O_3) at 0.5 µm, 0.68 µm and 0.91 µm and an increase of reflectance towards the SWIR range. This is due to the loss of water during the firing process that is applied to tiles within the manufacturing. Modern buildings are often covered by metal such as zinc. It shows a broad and deep absorption band at 1.02 µm (Figure 2).

A widespread synthetic roof material is polyethylene (PE) that is used especially for flat roofs. PE shows the highest reflectance values with deep and narrow absorption features at 1.2 µm and 1.7 µm that are caused by stretch vibrations of C-H compound (vi). Furthermore, there is a clear absorption feature at 2.17 µm and the sharp decrease of reflectance starting from 2.2 µm.

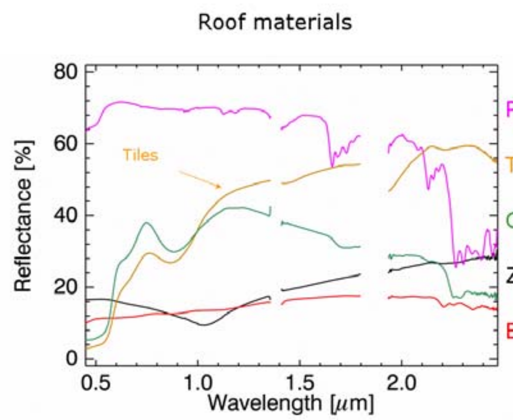

Figure 2: Spectral field and laboratory measurements of selective sealed surface materials.

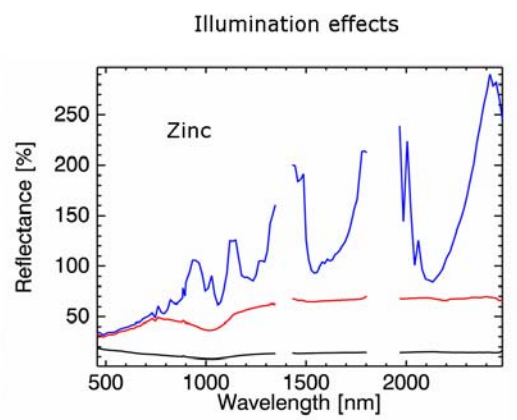

Figure 3: Spectral measurement of shaded zinc roof (black), illuminated zinc roof (red) and specular reflectance of a zinc roof (blue).

The results of the field data cannot be directly compared to hyperspectral image data, because of several parameters resulting in spectral variations. For the investigation of this effect a multitude of image spectra (samples) for each of the 21 fully and partially sealed surfaces of the test sites in Dresden and Potsdam was selected from the urban spectral library. It results in a total of 3414 sample spectra taking into account. Spectral variations have its seeds in material conditions (e.g. coating, degradation), illumination effects, sensor characteristics (e.g. signal to noise ratio) and data preprocessing (e.g. noise removal techniques, atmospheric corrections). The resulting variations can significantly alter the spectral signal.

The effects of different illumination situations have been investigated using hyperspectral HyMap spectra. This way, several spectra of roofing tiles were selected from the image differing in the orientation towards sun and sensor. Although the albedo varies significantly, the roofing tiles can still be identified based on the spectral shape.

An exception is specular reflectance. This phenomenon is typical for metallic and glass materials. It leads to a complete change of the spectral signature that is shown for the roof material zinc in Figure 3. Measurements for the shaded and illuminated side of a zinc roof are characterized by the broad absorption feature at 1.02 µm. This characteristic disappears for the spectrum of a specular reflection, where the spectrum shows several strong absorption bands. It happens if the radiation exceeds the dynamic range of the sensor. As a result the detector records less energy compared to the real input and applying an atmospheric correction, the resulting reflection values will be underestimated. Reflection values in the wavelength ranges of atmospheric gases are correct, because these ranges are unaffected by saturation. The described specular characteristics depend only on the sensor.

The knowledge of the type and effect of such spectral variations is important for the determination of robust spectral features that is further described in the next chapter.

Robust features

Based on the 3414 sample spectra that were used to investigate spectral variations (see above) robust spectral features were selected. For each material specific reflectance features, the wavelength range of their occurrence and the used features functions are determined. The largest number of spectral features could be found for bright urban surface materials, such as polyethylene (PE), roofing tiles and concrete. In contrast, some of the dark materials, such as roofing tarpaper, slate and dark loose chippings show weak distinctive spectral features. For their separation from the other surface materials the brightness was used. The results for two selective examples are listed in Table 1. The wavelength values correspond to the center wavelength of the HyMap bands.

Table 1: Robust spectral features for selective sealed urban surface materials obtained from hyperspectral HyMap data.

Material (no. of sample spectra)	Spectral feature	Feature function (see also Figure 1)	Wavelength range [nm]
Tiles (357)	Absorption band	Absorption depth and position	457 - 580
	Increase	Ratio	517 - 2401
	Absorption band	Absorption depth and position	624 - 761
	Absorption band	Absorption depth and position	777 - 981
	Absorption band	Absorption depth and position	2132 - 2236
Bitumen (296)	Brightness	Mean, Standard deviation	447 - 2449
	Absorption band	Area	1028 - 1264
	Increase	Ratio, Offset + Gain + RMS of regression line	1163 - 1778
	Decrease	Ratio	2078 - 2201
Asphalt (240)	Brightness	Mean, Standard deviation	447 - 2449
	Constant reflectance	Offset + Gain + RMS of regression line	1163 - 1778
Dark loose chippings (110)	Brightness	Mean, Standard deviation	447 - 2449

Former investigations regarding differentiation of surface materials using hyperspectral image data showed that there are limitations in the differentiation between dark materials, such as asphalt and roofing bitumen (vii). However, spectral characteristics of bright roofing bitumen differ from asphalt due to several absorption features in the SWIR I and II range (Table 1). These characteristics can be expressed by ratios. Asphalt has no absorption bands and is characterized by a constant and slight increase of the reflectance. This feature is described by the offset, gain and RMS (root mean square error) of a regression line. However, due to the low albedo of the described materials, these features are strongly influenced by noise. In the next chapter, the visual selection of robust features is validated. The question is, are they appropriate to separate urban surface materials?

Separability analysis

The separability analysis is based on the calculation of the confusion matrix using the Parallel-Epiped classifier. The database for the separability analysis consists of the 3414 sample spectra obtained from hyperspectral image data and 2356 additional image spectra of shadow and water. These additional low reflectance spectra were introduced, because they show confusion with other dark materials. Due to their introduction, the separability analysis becomes more reliable. The ranges of the classes in the feature space were defined using 90 different features. These features are a result of the determination of robust features for each of the investigated urban surface materials.

Table 2: Results of the separability analysis for roof materials and materials of sealed open spaces.

Roof materials	Commission error [%]	Materials of sealed open spaces	Commission error [%]
PVC	0.0	Concrete	17.0
PE	0.0	Tartan	0.0
Gravel	1.2	Asphalt	7.1
Tarpaper	0.0	Pavement of concrete	10.0
Tiles (new and old)	0.0 (0.0)	Cobblestone pavement	5.0
Red concrete	0.0	Red loose chippings	3.4
Aluminum	0.0	Dark loose chippings	2.3
Zinc	0.0	Bright loose chippings	2.7
Copper	0.0		
Bright roofing bitumen	9.1		
Dark roofing bitumen	1.3		
Slate	0.0		

The results listed in Table 2 show a very good separability of classes based on their feature characteristics. From the 21 considered classes (surface materials), 11 classes could be identified without confusion resulting in a commission error of 0.0 %. Further 6 classes show a commission error equal and less than 5 %. The Table 1 shows that best results could be obtained for bright materials, such as polyvinyl chloride, red loose chippings and tartan. They are characterized by strong and distinct reflectance features. However, also dark materials with low albedo and weak reflectance features, such as roofing tarpaper and roofing bitumen, could be separated.

Larger confusion occurred for concrete (sealed open space), 11.7 % were also classified as roofing gravel. Although both surface classes are made of different materials, they have similar spectral features. In this case the differentiation based on the analyzed robust features is limited.

For the differentiation of bright roofing bitumen and asphalt the commission error amounts to only 9.1 % and 7.1 % vice versa. This is a very good result, having in mind that both surfaces are made of the same material differing only in different additives and use. Further 2.3 % of dark loose chippings were also identified as bright roofing bitumen. These results show that the presented feature-based approach in this paper also leads to good results even in case of dark materials.

CONCLUSIONS

An urban spectral library was developed containing field and image spectra for a wide range of urban surface materials that are characteristic for middle European cities. This library was the basis for the analysis of spectral characteristics and the variations of urban surfaces. For each of the sealed urban surfaces typical reflectance characteristics, such as broad absorption bands for zinc and other typical shape properties could be found. In hyperspectral image data, these typical spectral features are often be influenced by effects causing spectral variations. Parameters, such as specular reflectance, and shadows can lead to a strong variations. Other factors, such as different illumination and data preprocessing causes changes to the spectral characteristics to a lesser degree.

For each of the 21 sealed urban surfaces materials one or more robust spectral features could be determined. These features were quantitatively described using 11 feature functions. Best results could be obtained for bright materials due to their strong spectral characteristics. Spectral properties of dark materials could also be defined despite the weak spectral features caused by the low reflectance values of the materials. The validation shows also good separation even for materials with only one robust spectral feature. This way, using the selected 90 robust features the potential for differentiation of urban surface materials could be demonstrated. It has to be improved in case of materials such as roofing gravel and concrete by the determination of further distinctive feature.

However, a further increase of sample spectra limits the possibilities for visual extraction of robust spectral features. Thus, future investigations will focus on the automated extraction of robust spectral features. The described feature functions are an appropriate tool for their quantification. This concept can be expanded by new functions for a better description of distinct spectral features of urban materials. Simultaneously, the introduction of additional sample spectra from other test sites is possible and can improve the results.

The developed approach of this paper is of special importance for improved endmember detection in the process of automated differentiation of urban surfaces. Since endmembers should only contain spectrally pure pixels, the presented feature-based methodology can be used for their automated differentiation and identification. Urban materials can be identified in remote sensing data without introducing specific training information of a particular test site. This is an important step towards a fully-automated identification of urban surfaces based on hyperspectral remote sensing data. Such automated approaches are essential for the development of strategies allowing an effective monitoring of large urban areas.

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