

Urban Objects Classification by Spectral Library: Feasibility and Applications

Walid Ouerghemmi
Univ. Paris-Est,
LASTIG MATIS, IGN,
ENSG
F-94160, Saint Mandé,
France
Walid.ouerg@gmail.com

Sébastien Gadal
Aix-Marseille Univ, CNRS,
ESPACE UMR 7300,
Univ Nice Sophia Antipolis,
Avignon Univ
13545 Aix-en-Provence, France
sebastien.gadal@univ-amu.fr

Gintautas Mozgeris
and Donatas Jonikavičius
Aleksandras Stulginskis
University
LT-53361, Akademija, Kaunas
r., Lithuania
gintautas.mozgeris@asu.lt
donatas.jonikavicius@asu.lt

Christiane Weber
UMR TETIS,
AgroParisTech-Irstea-
Cirad/CNRS
34000, Montpellier,
France
christiane.weber@teledet
ection.fr

Abstract— Objects recognition in urban environment using multiband imagery is a difficult process, implying the use of elaborated and complex image processing methods, which are used to enhance the detection efficiency. The urban mosaics are characterized by multiple materials (e.g. manmade, urban vegetation, bare soil, transport infrastructure, etc.), which are combined together to form a complex patchwork. This study aims to take advantage of the multiband imagery, to assess the feasibility degree of the urban objects detection, and to explore some of the applications related to the multiband hyperspectral imagery classification.

I. INTRODUCTION

The development of Hyperspectral sensors over the last years, gives a great opportunity to characterize terrestrial objects precisely, thanks to the high spectral resolution of these sensors. The hyperspectral imagery is increasingly used in many fields [1], [2]; mineral mapping, agronomic/urban monitoring, gas detection, etc. The interest in hyperspectral imagery is growing and many methods and technics are developed to process these data, including morphological profiles [3], Markov chain [4], etc. In this study we present an urban objects characterization method using airborne hyperspectral imagery. The urban context is characterized by a high heterogeneity between the objects surface [5], [6], and the uses of classification techniques (e.g. spectral/spatial based classifier) could be challenging, due to the non-existence of reliable training samples, and the high spectral correlation between the spectral signatures e.g. [7], [8]. Thus, we propose to classify the urban objects using a spectral library of urban objects, and to rectify the classification results using geometric attributes [9], [10], to compensate the spectral correlations between urban materials. The use of such technique could be useful in detecting some specific objects from the scene of interest, when applying a spectral classification. The goal is to

discern efficiently terrestrial objects in a high heterogeneous context.

II. HYPERSPECTRAL CAPTURE OF DENSE URBAN CITY CENTER

For this study, two datasets are used; 1) a hyperspectral image captured in Kaunas city center (Lithuania), in July 2015, using the Finnish frame hyperspectral imager RIKOLA (Vis-NIR), (see [11], for more details about the camera and the acquisition process). The airborne imager was configured to produce 16 bands, with a spectral range of 400-900nm and a spatial resolution of 0.7 meter; the mean aircraft altitude was equal to 1000 meter during the flight mission, and 2) an urban spectral library measured with the hyperspectral laboratory camera Themis-Vision VNIR400H. The sensor was developed by the US Company Themis Vision Systems LLC 2011, and is able to measure the electromagnetic radiation from 400 nm to 900 nm using 1024 narrow bands; the spectral resolution is equal to 0.6 nm. For our study we have used 3 hyperspectral test zones, extracted from the RIKOLA image, concerning different urban areas over the city of Kaunas (Fig. 1).

The spectral library is divided into 2 groups of urban materials; a first group collected and measured over the city of Kaunas in July 2015, and a second group of urban materials, coming from the Kaunas University of Technology (KTU, department of materials), and measured by our laboratory imaging camera, using 955 bands from 400nm to 1000nm, with a spectral resolution of 0.6nm. Kaunas city is characterized by an interesting heterogeneity in terms of manmade materials, roads and vegetation species. This study concerns the manmade materials detection, the city is composed essentially of tile, metal, asbestos, and bitumen roofing's, in addition to the asphalt, pavements, and stony roads.

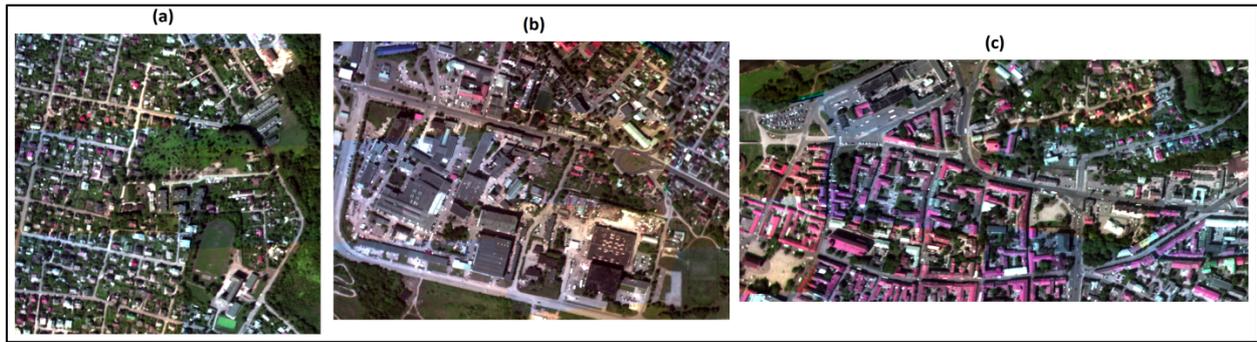


Fig. 1. True color images over (a) residential zone, (b) industrial zone, and (c) Historical center of Kaunas city.

III. URBAN OBJECT CLASSIFICATION BY HYPERSPECTRAL LIBRARY

The hyperspectral image was converted to reflectance using QUAC tools [12]. The first step concerns the spectral classification, which is carried using the Spectral Angle Mapper methods [13], the training samples were extracted from our spectral library; each sample is an average spectrum of multiple spectra of the same material (i.e. the average is calculated over 10 or 5 spectra depending on the available data). A custom Max angles were used for spectral matching by SAM measure to compensate the use of an external library instead of image based spectra. In addition to these data, we have used a Geographic Information system to validate the classification results (i.e. Fig. 2).

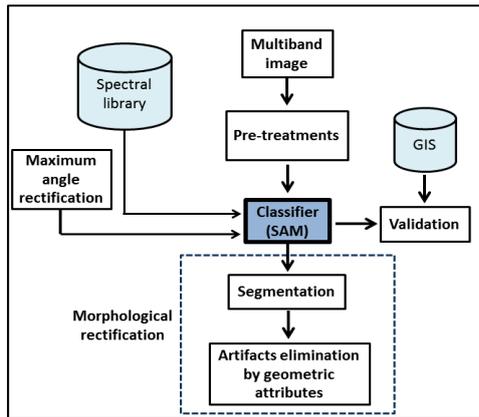


Fig. 2. Urban objects classification by spectral library and morphological rectification of multiband image.

Once the spectral classification done, a segmentation is applied on each class vector, and the different objects are extracted and their geometric attributes measured (i.e. area, elongation, convexity, circularity, etc.), the last step consists, in filtering the misclassified pixels, by the geometric attributes, and/or by a group of attributes (i.e. Fig. 2). The methodology is inspired by the framework proposed in [14]. The objects detection was carried over grey-scale class images by manual thresholding segmentation; the processing interval was determined by the images histograms [15], the attributes generation was performed using Aphelion® software (ADCIS, AAI INC).

The use of spatial information for objects detection using multi-bands imagery, have been investigated and proven to be useful, nevertheless, the objects detection by combined attributes was less addressed; e.g. in [16] geometric attributes were combined with Binary Partition tree using object-oriented pruning, to detect roads and building (area and elongation attributes were used).

IV. SPECTRAL VARIABILITY

In this section, a variability study is carried to extract 1) the interclass spectral similarity between urban common materials and 2) the intraclass spectral similarity between n samples belonging to the same material. We used 9 groups of urban materials commonly used in the city of Kaunas (tile, bitumen, asbestos, dark painted metal, clear painted metal, red painted metal, clear painted fiber cement, asphalt, pavements), each group is composed of 5 to 10 spectra, depending on the available data per material. The interclass correlation is measured between the groups of materials using an averaged spectrum per group. The intraclass correlation is measured between the available spectral samples of each group of materials.

The interclass correlation is showed for tile and asbestos materials in TABLE I, the presence of high interclass correlations could affect the spectral classification efficiency, and produce misclassifications between the classes. Nevertheless, the global interclass correlation variability still acceptable (i.e. Max = 97%, Min = 40% and SD = 0.15), and enforces the hypothesis of a reasonable heterogeneity degree between the materials.

Concerning the intraclass correlation, the correlation values are extracted in TABLE II, with Maximum correlation, minimum correlation, and standard deviation, for each material. The tile, fiber cement, red painted metal and pavements, present the lower standard deviation which mean that the intraclass correlation for these materials is low (i.e. small gap between Max and Min correlations), thus, their spectral variability is low, and they present a low risk to be misclassified. The remaining materials have a higher standard deviation, which result in a higher intraclass correlation (i.e. wide gap between Max and Min correlations), and a higher spectral variability, these materials present a high risk to be misclassified.

TABLE I. Interclass correlation table (i.e. measured for 2 materials)

	Intercalss correlation table per material								
	Tile	Bitumen	Asbestos	Dark painted metal	Clear painted metal	Fiber cement	Asphalt	Red painted metal	Pavements
Tile	100%	94%	89%	82%	74%	87%	72%	93%	96%
Asbestos	89%	81%	100%	77%	40%	72%	43%	88%	97%

TABLE II. Intraclass correlation table of urban materials

Measured specs	Intraclass correlation per group of materials								
	Tile	Bitumen	Asbestos	Dark painted metal	Clear painted metal	Fiber cement	Asphalt	Red painted metal	Pavements
Max correlation	99%	98%	99%	92%	98%	98%	96%	99%	98%
Min correlation	98%	67%	78%	61%	63%	95%	80%	99%	96%
Standard Deviation	4.10^{-4}	$9.8.10^{-3}$	$4.7.10^{-3}$	$8.7.10^{-3}$	$7.9.10^{-3}$	$8.7.10^{-4}$	$6.6.10^{-3}$	$7.8.10^{-5}$	$8.1.10^{-4}$

V. EFFICIENCY OF URBAN OBJECTS RECOGNITION

Concerning the residential zone (i.e. Fig.3.a), the clear painted metal, and red painted metal roofing's, were well distinguished, the asbestos roofing's were partially identified, but presenting high correlation with roads and some bitumen roofing's, the overall accuracy and Kappa coefficient are respectively of 33% and 0.22, the performance is essentially weakened due to small size of the objects of interest. Concerning the industrial zone (i.e. Fig.3.a), the bitumen roofing's which compose most of the scene (i.e. soft grey bitumen type, Fig 1.b) were well distinguished by our spectral library, with a visible correlation with asphalt roads, the identified bitumen type

matched the scene among 4 other bitumen of the spectral library, the other bitumen type (dark bitumen type, Fig 1.b bottom right) cannot be identified by the library, clear painted metal, red painted metal, and tile roofing's were also well identified, asbestos roofing's were partially identified and presenting high correlation with pavements, the overall accuracy and Kappa coefficient are respectively of 67% and 0.44, which is an acceptable classification performance. Concerning the historical center of Kaunas city, we have almost a good identification of all the materials, with a correlation of the bitumen and asbestos with roads, the overall accuracy and Kappa coefficient are respectively of 73% and 0.56, this latter scene, gives the best classification performance, due to a more consistent ground truth data.

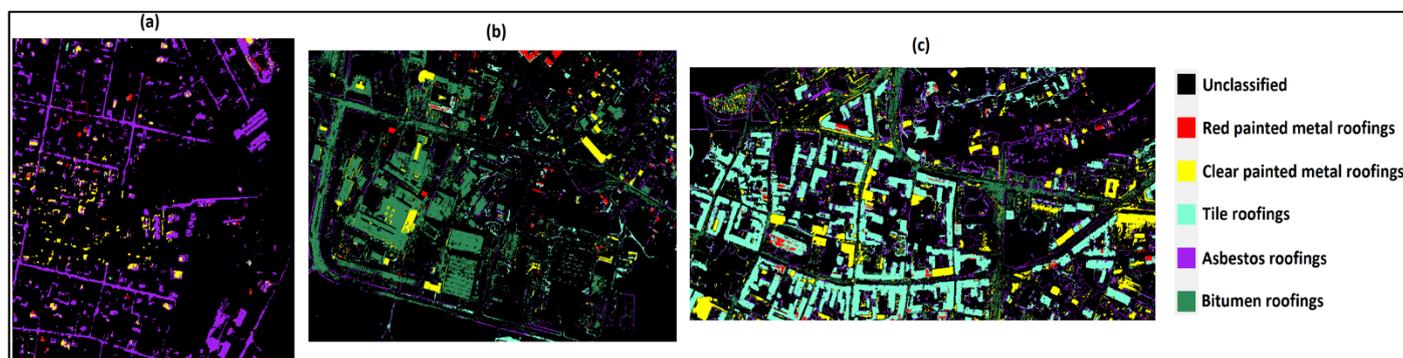


Fig. 3. Spectral classification by spectral library of (a) residential zone, (b) industrial zone, and (c) Historical center of Kaunas city.

After the spectral classification, a morphological rectification was carried over the classified image to enhance the objects detection, and to minimize the misclassifications. The first step of this rectification, consists in segmenting each vectorized class into objects, the geometric attributes of each object (i.e. group of pixels) are then generated and used to eliminate the misclassified pixels. Let's consider the industrial zone example before rectification (Fig 4.a); an important misclassification of the asbestos and bitumen type roofing with asphalt roads and pavements is noticed, in addition to the presence of artefacts. Fig 4.b shows the classification enhancements

after morphological rectification; the roads and artefacts were eliminated, using simple and combined rules.

Concerning the roads detection; elongation and [circularity + elongation] attributes performed well; the elongation was used for roads segments detection, the circularity was added to detect circular roads portions, (Fig. 4.b). Concerning the artefacts detection, area and [convexity + area] attributes performed well; the area was used for lines type artefacts detection (i.e. few pixels), the convexity was added for complex type artefacts detection, other rules could be used to eliminate further objects (e.g. irregular roads, perpendicular roofs, trees).

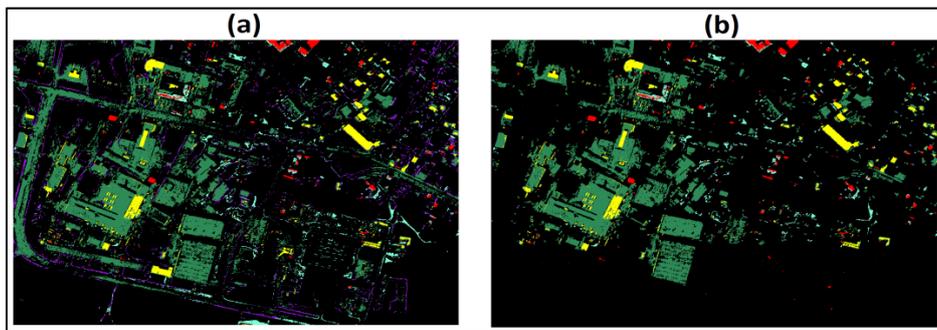


Fig. 4. Morphological rectification by geometric attributes, (a) image of industrial zone before rectification, and (b) image of the same zone after rectification.

VI. CONCLUSION

An original technique based on the urban objects identification by spectral library, using airborne hyperspectral imagery, is presented in this study. The potential to distinguish some of the common roofing's materials in the city of Kaunas was demonstrated. Nevertheless, some issues need to be addressed in the future, as the high interclass and intraclass correlations regarding some urban materials, leading to misclassifications. Asbestos type roofing's and bitumen roofing's were difficult to identify and presents high correlation with the other materials like asphalt roads and pavements. To improve the spectral classification results, we proposed a morphological rectification based on attributes filtering, and rules construction, the rectification seemed suitable, and permits to eliminate the misclassified pixels (i.e. artefacts, roads, shadows, etc.). For the future, we are planning to 1) enrich the spectral library with more materials, 2) test other datasets including more bands, and 3) use other classifiers (e.g. SVM, neural networks).

Acknowledgment

This research was supported by the French National Research Agency (ANR) through the HYP project (ANR-14-CE22- 0016).

References

- [1] A. Plaza, J. A. Benediktsson, J. W. Boardman, J. Brazile, L. Bruzzone, G. Camps-Valls, J. Chanussot, M. Fauvel, P. Gamba, A. Gualtieri, M. Marconcini, J. C. Tilton, and G. Trianni, "Recent advances in techniques for hyperspectral image processing," *Remote Sensing of Environment*, vol. 113, Supp 1, pp. S110–S122, 2009.
- [2] F. A. KRUSE, "Identification and mapping of minerals in drill core using hyperspectral image analysis of infrared reflectance spectra," *International Journal of Remote Sensing*, vol. 17, no. 9, pp. 1623–1632, 1996.
- [3] M. Fauvel, J. A. Benediktsson, J. Chanussot and J. R. Sveinsson, "Spectral and Spatial Classification of Hyperspectral Data Using SVMs and Morphological Profiles," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 46, no. 11, pp. 3804–3814, 2008.
- [4] J-B. Courbot, E. Rust, E. Monfrini, and C. Collet, "2-Step Robust Vertebra Segmentation," *International Conference on Image Processing Theory, Tools and Applications*, Orléans, France, Nov. 2015.
- [5] S., Gadal, and W., Ouerghemmi, "Morpho-Spectral Recognition of Dense Urban Objects by Hyperspectral Imagery," *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 40(3), 433, 2015.
- [6] A. Hervieu, A. Le Bris and C. Mallet, "Fusion of multispectral and hyperspectral aerial image classifications in urban areas," *ISPRS Annals of Photogrammetry, Remote Sensing and the Spatial Information Sciences*, Vol. III-3, Prague, Czech Republic, July 2016.
- [7] J. M. Bioucas-Dias, A. Plaza, N. Dobigeon, M. Parente, Q. Du, P. Gader, and J. Chanussot, "Hyperspectral unmixing overview: Geometrical, statistical, and sparse regression-based approaches," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 5(2):354–379, Apr. 2012.
- [8] C. M. Bachmann, T. L. Ainsworth, and R. A. Fusina, "Exploiting manifold geometry in hyperspectral imagery," in *IEEE Transactions on Geoscience and Remote Sensing*, 43(3):441–454, Mar. 2005.
- [9] P.A., Longley, and V., Mesev, "Measuring Urban Morphology using Remotely-Sensed Imagery", in: J. P. Donnay, M. J. Barnsley, and P. A. Longley, (eds.) *Remote Sensing and Urban Analysis: Volume 1*. CRC Press – Taylor & Francis: London, UK, pp. 148–168, 2000.
- [10] B. Song, J. Li, M. Dalla-Mura, P. Li, A. Plaza, J. M. Bioucas-Dias, et al., "Remotely sensed image classification using sparse representations of morphological attribute profiles", *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 8, pp. 5122–5136, Aug. 2014.
- [11] G. Mozgeris, S. Gadal, D. Jonikavicius, L. Straigyte, W. Ouerghemmi, and V. Juodkienė, "Hyperspectral and color-infrared imaging from ultra-light aircraft: Potential to recognize tree species in urban environments," *8th Workshop in Hyperspectral Image and Signal Processing: Evolution in Remote Sensing*, Los Angeles, USA, Aug. 2016.
- [12] L. S., Bernstein, S. M. Adler-Golden, R. L. Sundberg, et al, "Validation of the QUick Atmospheric Correction (QUAC) algorithm for VNIR-SWIR multi- and hyperspectral imagery," *SPIE Proceedings, Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XI*. Vol. 5806, pp. 668–678, 2005.
- [13] Kruse, F. A., A. B. Lefkoff, J. B. Boardman, K. B. Heidebrecht, A. T. Shapiro, P. J. Barloon, and A. F. H. Goetz, "The Spectral Image Processing System (SIPS) – Interactive Visualization and Analysis of Imaging spectrometer Data," *Remote Sensing of Environment*, v. 44, p. 145 – 163, 1993.
- [14] S. Gadal et W. Ouerghemmi, "Morpho-spectral objects classification by hyperspectral airborne imagery," *8th Workshop in Hyperspectral Image and Signal Processing: Evolution in Remote Sensing*, Los Angeles, USA, Aug. 2016.
- [15] M. Sezgin, "Survey over image thresholding techniques and quantitative performance evaluation," *Journal of Electronic imaging*, vol. 13, no. 1, pp. 146–168, 2004.
- [16] J. A. Benediktsson, L. Bruzzone, J. Chanussot, M. Dalla Mura, P. Salembier, S. Valero, "Hierarchical analysis of remote sensing data: Morphological attribute profiles and binary partition trees", in: ISMM, International Symposium on Mathematical Morphology, Proceedings, Lecture Notes in Computer Science, pp. 306–319, Springer, 2011.