FUSION OF LIDAR AND RADAR DATA FOR LAND-COVER MAPPING IN NATURAL ENVIRONMENTS

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ABSTRACT

Land-cover geodatabases are key products for the understanding of environmental systems and for setting up national and international prevention and protection policies. However, their automatic generation and update remain complicated with high accuracy over large scales. In natural environments, most of the existing solutions are semi-automatic in order to achieve a suitable discrimination of the large number of forest and crop classes. A large amount of remote sensing possibilities is at the moment available and data fusion appears to be the most suitable solution for that purpose. The paper tackles the issue of land-cover mapping in such areas assuming the existence of a partly non-updated 5-class geodatabase: *buildings, roads, water, crops, forests*. Lidar point clouds and Radar images at two spatial resolutions and bands are merged at the feature level and fed into an efficient supervised classification framework. Results show that some classes benefit from the joint exploitation of multiple observations in terms of accuracy or recall.

Index Terms— land-cover, lidar, radar, classification, fusion, features, natural environments.

1. INTRODUCTION

Airborne lidar and Radar have become, during the last decade, established remote sensing techniques that provide invaluable inputs for the discrimination of various surface types, and more generally to land-cover (LC) mapping [1]. In particular, they have been recently introduced for addressing 2D LC geodatabase change detection and updating issues since they complement very well geospatial (airborne/satellite) optical very high resolution images. However, in the large body of literature of remote sensing data fusion, two main limitations currently exist.

First, fostering information extraction from optical images and proposing advanced fusing methods are main topics of interest to the detriment of feature extraction from lidar and Radar data [2]. Consequently, only few papers try to generate a large number of attributes and to assess their relevance for land-cover discrimination [3]. Even when such a step is performed, it is often limited to standard topographic objects

(vegetation, buildings, roads). Therefore, studies are tailored to very specific classes [4], and most of the time to the detriment of natural environments, where a high complexity of appearances prevails.

Secondly, merging lidar and Radar data has been barely addressed and limited to few issues: large-scale forest monitoring and biomass estimation [5, 6], Digital Elevation Model generation [7], and interferometry purposes [8]. Furthermore, among these works, only few consider these two data sources at the same level e.g., at the feature or the decision levels.

In this paper, we propose to investigate the relevance of VHR airborne lidar and (polarimetric) Radar data fusion at the feature level in order to discriminate the five main land-cover classes (namely *buildings, roads, water, forests, and crops*). For that purpose, we focus on extracting a comprehensive and versatile set of features from both data sources. These features are then fed into a supervised classification framework involving Random Forests with a novel decision fusion process, adapted from [9].

2. MATERIAL

The area of interest is located around the city of Tarbes, South-West of France, over 16 km². It is a rather challenging peri-urban area since it exhibits many land-cover and land-use classes around a dense city center.

2.1. Land-cover geodatabase

Five general classes of interest are considered for this study: *buildings, roads, water, forests, and crops*. It corresponds to a simplification of the newly established French land-cover 2D database, natively composed of 23 classes [9]. Such database was generated in 2013 with the fusion of various existing national vector datasets and then refined and corrected by human operators. These polygons are used both for learning the appearances of the objects and for validating the results (see Section 3). Therefore, we assume that no errors exist in term of geometry and semantics, even if our method is able to deal with spatial and semantic discrepancies between the input image and the DB [9]. The main challenge with such a simplified LC database lies on the significant heterogeneity

of appearances inside each class: various building and road materials, lake and river, many tree species and crops. Such challenge is exacerbated by the temporal shift between the three data sources introduced in this study (see below).

2.2. Lidar data

3D lidar point clouds have been acquired from an airborne platform for topographic purposes (*i.e.*, Digital Terrain Model - DTM - generation) using an Optech 3100 device. Data was collected in January 2013 with a point density ranging from 1 to 4 points/m² over 66km²: these are the specifications for French nation-wide mapping. Aside from the 3D coordinates of each point, the echo type (first, intermediate, last, single return), the number of returns for the emitted pulse and the intensity value (uncalibrated) were recorded. This allows to have a full description of the 3D structure of the trees, especially since we are under leaf-off conditions. In addition to the 3D point cloud, a 1 m DTM is provided and used for computing several features. It was automatically computed with TerraSolid softwares and a height accuracy of 0.5 m is guaranteed. No further quality assessment was performed.

2.3. Radar data

For our study, two Radar images at two distinct spatial resolutions and wavelengths were used, namely RADARSAT-2 and TerraSAR-X. They were acquired in April and August 2014, selecting the Quad Mode and the SpotLight product, respectively. RADARSAT-2 operates in the C band with full polarimetry, whereas only HH and VV polarisations were available for TerraSAR-X. Ground range/azimuth pixel sizes are 10.98/4.7m and 1.57/3.2m, respectively. The X band does not penetrate volumes and cross-polarised signals are backscattered for fully grown croplands for both C and X bands [10].

3. METHODS

3.1. General overview

We adopt the framework proposed in [9] for LC-DB updating, that can more generally be employed for land-cover mapping. A feature set is generated for each data source for the area of interest and used for subsequent classifications (see Section 3.2). All features are interpolated on a regular grid, compatible with the spatial accuracy of the existing LC-DB. Here a 1 m × 1 m grid is selected, and each cell has a unique label. Classification is operated as follows:

1. A supervised classification of the full area is performed for each 2D polygon of each of the 5 classes of the LC-DB. An iterative procedure was proposed in [9] in order to select the best training pixels for this binary classification task. A confidence value accompanies each label.
2. A class-level confidence map is then generated, following the experiments of [11]. A unique confidence value $\mathcal{P}$ is assigned for each pixel, stacking the confidences stemming from all the objects of the class. We have:
$$\mathcal{P}^C = \frac{1}{\sum_{O \in C} f_O} \sum_{O \in C} f_O \times \mathcal{P}_O^C, \quad (1)$$

where $\mathcal{P}_O^C$ is the confidence value of object O in class C and f_O its associated f-score value. The f-score metrics is inserted here in order to take into account both precision and recall values for each object and subsequently alleviate the influence of objects that do not help discriminating the other ones of the same class.
3. Eventually, a unique label is assigned to each pixel of the grid. It corresponds to the class with the highest $\mathcal{P}^C$ value.

A Random Forest classifier is adopted in order to efficiently deal with a high number of (multi-source) features and to be able to perform a large number of classifications in reduced computing times.

Three scenarios are tested, corresponding to three distinct feature sets, described below: Lidar, Radar (gathering features extracted both for RADARSAT-2 and TerraSAR-X), and Lidar+Radar.

3.2. Feature extraction

106 features are computed for each pixel of the grid: 72 are extracted from lidar data and 34 from Radar images.

3.2.1. Lidar features

They are generated from the 3D lidar point clouds using various environments with fluctuating sizes (*i.e.*, solutions for retrieving 3D points in a close neighborhood for computing local features, here 1 and 5 m), and various information: 3D coordinates, echo type and number, and intensity. They are tailored for retrieving planar objects, items with significant height variations, with low point densities for measuring the thickness of the vegetation layers or the range to the ground surface etc [12, 13]. They can be segmented into three main categories:

- Point-based: the local geometry around each 3D point is analysed;
- Neighborhood-based: the variations in height and intensity in spherical and cylindrical environments are retrieved using various filters (moments, percentiles, contrast, etc.);
- Histogram-based: height and intensity histograms are computed for 5 m cylindrical neighborhoods in order to find the main peaks, and for the height information, to retrieve the number, characteristics, and differences between existing object layers.

Point-cloud based features are then projected on the 1 m regular grid and the mean value is selected when multiple points fall in the same cell.

3.2.2. Radar attributes

RADARSAT-2 image was first filtered using a BoxCar filter to reduce speckle. Then, several decompositions were performed, namely Pauli, Cloude-Pottier (H , A , α), and Freeman [14]. Additional eigenvalue features were computed (polarisation asymmetry and fraction, radar vegetation index and pedestal height), leading to 25 attributes [15]. Since only 2 polarisations were available for TerraSAR-X data, HH and VV intensities were simply used. They were computed for various window sizes ($3 \times 3 \rightarrow 13 \times 13$).

4. RESULTS

Classification results are summarized in Table 1, for the three tested scenarios. Overall accuracy is provided for each of the five classes as well as recall and precision. One can see that data fusion leads to two main behaviours. First, accuracy is slightly increased when merging the two feature sets. This is true for classes with high recall or accuracy for both data sources (mainly *crops*, *roads* and *buildings*). This shows their complementary. Secondly, accuracy can be decreased when a feature set does not help discriminating specific classes. Recall values are lower for *buildings* and *roads* and accuracy for *forests* and *crops*. Here, this is due to the low performance of Radar data. This comes from the fact that small patterns such as building, rivers or roads may not be correctly discriminated with RADARSAT-2 images due to the significant spatial resolution difference. TerraSAR-X data cannot help since very few features were extracted from HH and VV intensities. Furthermore, polarimetric decompositions are highly meaningful for segmenting the different scattering behaviours existing in natural environments. However, they cannot always be straightforwardly linked to thematic classes, especially for natural classes (*crops* and *forests*), which behaviours may fluctuate with the period of the year and their structure. Finally, the lidar feature set was designed so as to handle specific patterns and various classes within the same neighborhood, which was not carried out for the Radar one and may lead to additional confusion.

Quantitatively, one can see in Figure 1 that results are visually satisfactory and that the introduction of Radar data allows decreasing the confusion between crops and roads while eroding smallest patterns such as isolated buildings roads or tree hedges. Finally, it can be noticed that the qualitative analysis is limited by the specifications of the input LC-DB where these small elements are not existing.

	Lidar	Radar	Lidar+Radar
<i>Overall accuracy</i>			
	0.71	0.52	0.72
<i>Recall per class</i>			
Building	0.58	0.18	0.45
Road	0.54	0.24	0.47
Water	0.74	0.27	0.75
Forests	0.71	0.07	0.72
Crops	0.79	0.77	0.85
<i>Accuracy per class</i>			
Building	0.65	0.52	0.74
Road	0.50	0.34	0.63
Water	0.24	0.19	0.23
Forests	0.44	0.11	0.38
Crops	0.90	0.74	0.87

Table 1. Overall and per-class accuracies for the feature sets.

5. CONCLUSION AND PERSPECTIVES

This papers proposed a first step towards lidar and radar data fusion in natural environments at the feature level. Results shows our land-cover classification method is able to handle multi-source data and that fusion is beneficial for *forest* and *crop* classes. No genuine conclusion was drawn for *road* and *building* classes since without appropriate unmixing method, no full-polarimetric Radar image spatially compatible with these objects of interest was available. Future research will consist in designing a more consistent Radar feature set and in assessing the relevance of a comprehensive set of optical image-based, lidar, and Radar attributes for the 5 classes of interest as well as for the 23 initial classes. These improvements will be embedded in the pipeline presented in [11], which will also include optimized fusion at the decision level.

6. ACKNOWLEDGMENTS

The authors would like to thank Sébastien Giordano (ENSG) for fruitful discussions on the topic and DLR for providing the TerraSAR-X image under the LAN2595 project.

7. REFERENCES

- [1] I. Manakos and M. Braun, Eds., *Land Use and Land Cover Mapping in Europe. Partice & Trends*, Springer, 2014.
- [2] C. Berger, M. Voltersen, R. Eckardt, J. Eberle, T. Heyer, N. Salepci, S.Hese, C. Schmullius, J. Tao, S. Auer, R. Bamler, K. Ewald, M. Gartley, J. Jacobson, A. Buswell, Q. Du, and F. Pacifici, "Multi-Modal and Multi-Temporal Data Fusion: Outcome of the 2012 GRSS Data Fusion Contest," *IEEE JSTARS*, vol. 6, no. 3, pp. 1324–1340, 2013.

- [3] S. Hese, M. Lindner, M. Voltersen, and C. Berger, "TerraSAR-X and RapidEye data for the parameterisation of relational characteristics of urban ATKIS DLM objects," *ISPRS Archives*, vol. XXXVIII-4/W19, 2011.
- [4] V. Poulain, J. Inglada, M. Spigai, J.-Y. Tourneret, and P. Marthon, "High-Resolution Optical and SAR Image Fusion for Building Database Updating," *IEEE TGRS*, vol. 49, no. 8, pp. 2900–2910, 2011.
- [5] P. Hyde, R. Nelson, D. Kimes, and E. Levine, "Exploring LiDAR-RaDAR synergy- Predicting aboveground biomass in a southwestern ponderosa pine forest using LiDAR, SAR and InSAR," *Remote Sensing of Environment*, vol. 106, no. 1, pp. 28–38, 2007.
- [6] T. Fatoyinbo, R. Rincon, D.J. Harding, C. Gatebe, K.J. Ranson, G. Sun, P. Dabney, and M. Roman, "The 2011 Eco3D flight campaign: Vegetation structure and biomass estimation from simultaneous SAR, lidar and radiometer measurements," in *IGARSS*, 2012.
- [7] P. Gamba, F. Dell'Acqua, and B. Houshmand, "Comparison and fusion of LiDAR and InSAR digital elevation models over urban areas," *International Journal of Remote Sensing*, vol. 24, no. 22, pp. 4289–4300, 2003.
- [8] E. Heggy, M. Sedze, F. Bretar, S. Jacquemoud, P.A. Rosen, K. Wada, and T. Staudacher, "Coupling polarimetric l-band insar and airborne lidar to characterize the geomorphological deformations in the Piton de la Fournaise volcano," in *IGARSS*, 2010.
- [9] A. Gressin, N. Vincent, C. Mallet, and N. Paparoditis, "A unified framework for land-cover database update and enrichment using satellite imagerys," in *ICIP*, 2014.
- [10] F. Baup, R. Fieuzal, B. Mingam, A. Lopes, R. Fjortoft, C. Marais-Sicre, J.F. Dejoux, M. Zribi, N. Baghdadi, and E. Ceschia, "Contribution of ALOS, RADARSAT-2 and TerraSAR-X radar data for monitoring agricultural surfaces," in *IGARSS*, 2012.
- [11] A. Gressin, C. Mallet, M. Paget, C. Barbanson, P.L. Frison, J.P. Rudant, N. Paparoditis, and N. Vincent, "Un-sensored Very High Resolution Land-Cover mapping," in *IGARSS*, 2015.
- [12] D. Jaskerniak, P.N.J. Lane, A. Robinson, and A. Lucieer, "Extracting lidar indices to characterize multi-layered forest structure using mixture distribution functions," *Remote Sensing of Environment*, vol. 115, pp. 573–585, 2010.
- [13] C. Mallet, F. Bretar, M. Roux, U. Soergel, and C. Heipke, "Relevance assessment of full-waveform lidar data for urban area classification," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 66, no. 6, pp. S71–S84, 2011.
- [14] E. Pottier and J.-S. Lee, Eds., *Polarimetric RADAR imaging: from basics to applications*, CRC Press, 2000.
- [15] J.S. Lee, M.R. Grunes, T.L. Ainsworth, L. Du, D.L. Schuler, and S.R. Cloude, "Unsupervised Classification of Polarimetric SAR Imagery Based on Target Decomposition and Wishart distribution," *IEEE TGRS*, vol. 37, no. 5, pp. 2249–2258, 1999.

Fig. 1. Results over part of the area of interest (3km×2.5km). From top to bottom: airborne image ©IGN – Land-Cover database – Lidar classification – Lidar+Radar classification. ■: Building – ■: Road – ■: Water – ■: Forests – ■: Crops.