Contents

1 Introduction

1.1 Study of forested areas

Forests are an important component of planet's life. They represent 30% of the world land surface. They also hold about 90% of terrestrial biodiversity. Forests are also benefit for the environment; they capt and store the CO_2 [Fah+10]. About 45% of the total global carbon is held by forests. They also filter dust and microbial pollution of the air [Smi12]. Finally, They also play an important role in hydrological regulation and water purification [Lem+08].

Forest are complex structures [Pom02], for which informations are needed for management. The information can be the tree species or the tree maturity of the forest. There are two ways to extract such information from forest; field inventory or remote sensing. The field inventories are very expensive to set up and are also not adapted for a national study. A more adapted to obtain such information is remote sensing since it allows to extract them at a large scale.

1.2 Remote sensing for forested areas

The analysis of forested areas from a remote sensing point of view can be performed at three different levels: pixel, object (mainly trees) or stand. In statistical national forest inventory (NFI), an automated and accurate tree segmentation is needed in order to extract tree level features (basal area, dominant tree height, etc., [Mea+00; KM06]). However, the tree level is not the only reliable level of analysis for forest studies. When a joint mapping and statistical reasoning is required (e.g., land-cover (LC) mapping and forest inventory), forest stands remain the prevailing scale of analysis [Mea+00; Whi+16]. A stand can be defined in many different ways in terms of homogeneity: tree specie, age, height, maturity, and its definition varies according to the countries.

From a remote sensing point of view, the delineation of the stands is a segmentation problem. Forest stands are interesting in order to extract reliable and statistically meaningful features and to provide an input for multi-source statistical inventory. For land-cover mapping, this is highly helpful for forest database updating [KMW09], whether the labels of interest are *vegetated areas* (e.g., *deciduous/evergreen/mixed/non-forested)*, or, more precisely, the tree species. Most of the time in national forestry inventory institutes, for reliability purposes, each area is manually interpreted by human operators with very high resolution (VHR) geospatial images focusing on the infra-red channel [KM06]. This work is extremely time consuming and subjective [Wul+08]. Furthermore, in many countries, the wide variety of tree species (e.g., >20) significantly complicates the problem. The design of an automatic procedure based on remote sensing data would fasten such process. Additionally, the standard manual delineation procedure only takes into account the species, and few characteristics (alternatively height, age, stem density or crown closure), while an automatic method could offer more flexibility and would allow to combine characteristics extracted from all complementary data sources.

The use of remote sensing data for the automatic analysis of forests has been growing in the last 15 years, especially with the synergistic use of airborne laser scanning (ALS) and optical VHR imagery (multispectral imagery and hyperspectral imagery) [TMS14; Whi+16]. They appear to be both well adapted and complementary inputs for stand segmentation [DBG12; Dal+15; Lee+16]. ALS provides a direct access to the vertical distribution of the trees and to the ground underneath. Hyperspectral and multispectral images are particularly relevant for tree species classification: spectral and textural information from VHR images can allow a fine discrimination of many species, respectively. Multispectral images are often preferred due to their higher availability, and higher spatial resolution.

A prerequisite for data fusion is the most accurate alignment of the two data [TMS14]. A frequently used technique is to geo-rectify images using ground controls points (GCPS). A geometric transformation is established between the coordinates of GCPs and their corresponding pixels in the image. It is then applied for each pixel, so that coordinate differences on those checkpoints are reduced to the lowest possible level. This method can be easily applied and is relatively fast in terms of computation time. However the use of GCPs can still cause that the unknowns in the trajectory of the platforms produce some remarkable residual errors. Automatic methods for data registration have also been developed [Hab+05; MKF09].

1.3 Context of the thesis

In France, the study of forests is two fold. They need to be mapped and inventoried. The forest inventory allows to obtain the wood stock at a national scale. Statistics such as volume per hectare, deciduous volume or conifer volume can then be derived. The inventory is performed through field inventory and extrapolated using the forest mapping. Thus, the mapping of forest is very important in order to derive accurate statistics.
The forest mapping is given by a national forest LC database. It is manually interpreted by human operators with VHR infra-red colored (IRC) orthoimages. It assigns a vegetation type to each mapped beach of more than 5000 m^2. The nomenclature is composed of 32 classes based on hierarchical criteria such as pure stands of the main tree species of the French forest. The forest LC should be updated in a 10 years cycle.

1.4 Objectives

Currently, the forest LC is obtained through remote sensing (namely photointerpretation), an method could be developed to update it automatically. Since an old version of the forest LC is available, it can be used as a ground truth input subsequent classification [Gre+13]. However, the learning process should be carried out carefully [Gre+14b]. Indeed, some area might have change (e.g. forest cuts). Furthermore, the database is designed generalized [SS77]. A simple classification would then not be sufficient in order to retrieve homogeneous patches similar to the forest LC. Such results could be obtained using smoothing methods [Sch12]. Furthermore, an automatic method would allow to enrich the LC, i.e. retrieve homogeneous tree species stands also homogeneous in terms of height [Gre+14a].

1.5 Strategy

Two remote sensing modalities are available for the mapping of forested areas at IGN; VHR optical images and lidar cloud points. The VHR images are a part of a national database. In this thesis, the images used have a spatial resolution of 50 cm. Two type of ortho-images are available, a color image (3 bands; red: 600-720 nm, green: 490-610 nm and blue: 430-550 nm) and and IRC image (3 bands; near infra-red: 750-950 nm, red and green) captured by the IGN digital cameras [Sou+12]. It is then possible to obtain four band ortho-images by the combination of the two ortho-images type.
IGN also process lots of test flight over forested areas with a laser scanning device. The airborne lidar data were collected using an Optech 3100EA device. The footprint was 0.8 m in order to increase the probability to reach the ground. The point density for all echoes ranges from 2 to 4 points/m^2.

The registration between airborne lidar point clouds and VHR multispectral images was performed by IGN itself using ground control points. This is a standard procedure in the French mapping agency since IGN operates both sensors and has also a strong expertise in data georeferencing (this is in fact the national institute responsible for that in France for both airborne and spaceborne sensors).
Data were acquired under leaf-on conditions and fit with the standards used in many countries for large-scale operational forest mapping purposes.

The combination of these two data is very relevant for the study of forest, indeed, optical images provide the major information about the tree species, while lidar give information about the vertical structure of the forest. Furthermore, the lidar allows to extract consistent object such as trees.

In order to extract more information from these two modalities, the fusion should be performed at different levels. 3 levels could be defined:

- Low level: It corresponds to the fusion of the observations, in this case, only the reflectance from the optical images and the height of the lidar points.
- Medium level: It corresponds to the fusion of the features, they are derived at the same level (e.g. the pixel) and merged together. It also corresponds to the cooperative understanding of the data; a feature is derived on a modality (e.g. trees from lidar) and use on the other.
- High level: It corresponds to the fusion of decision. One or many classifications have been performed and the final decision is a smart combination of the classifications and the input data.

1.6 Structure of the thesis

- State of the art: Chapter 2
- Method: Chapter 3
- Results: Chapter 4
- Conclusion and perspectives: Chapter 5

2

State of the art

2.1 Stand segmentation

One should note that the literature remains focused on individual tree extraction and tree species classification, developing site-specific workflows with similar advantages, drawbacks and classification performance. More authors have focused on forest delineation [Eys+12], that do not convey information about the tree species and their spatial distribution. Consequently, no operational framework embedding the automatic analysis of remote sensing data has been yet proposed in the literature for forest stand segmentation [Dec+17].

In the large amount of literature in the field, only few papers focus on the issue of stand segmentation or delineation. They can be categorized with regard to the type of data processed.
First, stand segmentation can be achieved with a single remote sensing source. A stand delineation technique using VHR airborne multispectral imagery is proposed in [Lec+03]. The trees are extracted using a valley following approach and classified into 7 tree species (5 coniferous, 1 deciduous, and 1 non-specified) with a maximum likelihood classifier. A semi-automatic iterative clustering procedure is then introduced to generate the forest polygons.
A hierarchical and multi-scale approach for the identification of stands is adopted in [Her+12]. The data inputs were the 4 bands of an airborne 0.5 m orthoimage (Red, Green, Blue, and Near Infra-Red) allowing to derive the Normalized Difference Vegetation Index (NDVI). The stand mapping solution is based on the Object-Based Image Analysis concept. It is composed of two main phases in a cyclic process: first, segmentation, then classification. The first level consists in over-segmenting the area of interest and performing fine-grained land cover classification. The second level aims to transfer the vegetation type provided by a land cover geodatabase in the stand polygons, already retrieved from another segmentation procedure. The multi-scale analysis appears to have a significant benefit on the stand labeling but it is highly heuristic and requires a correct definition of the stand while we consider it is an interleaved problem.
A seminal stand mapping method using low density airborne lidar data

is proposed in [Koc+09]. It is composed of several steps of feature extraction, creation and raster-based classification. Forest stands are created by grouping neighboring cells within each class. Then, only the stands with a pre-defined minimum size are accepted. Neighboring small areas of different forest types that do not reach the minimum size are merged together to an existing forest stand. The approach offers the advantage of detecting 15 forest types that match very well with the ground truth but to the detriment of simplicity: the flowchart has to be highly reconsidered to fit to other stand specifications. Additionally, the tree species discrimination is not addressed.

The forest stand delineation proposed in [Sul+09] also uses low density airborne lidar still coupling an object-oriented image segmentation and a supervised classification procedure. Three features are computed and rasterized. The segmentation is performed using a region growing approach. Spatially adjacent pixels are grouped into homogeneous discrete image objects or regions. Then, a supervised discrimination of the segmented image is performed using a Battacharya classifier, in order to determine the maturity of the stands. The tree species are ignored and the procedure requires a careful inspection of the raw data both for feature generation and model training.

Following the work of [Wul+08] with IKONOS images, Quickbird-2 panchromatic images are used in [MWW10] to automatically delineate forest stands. A standard image segmentation technique is used and the novelty mainly lies on the fact that its initial parameters are optimized with respect to NFI protocols. They show that meaningful stand heights can be derived, which are a critical input for various modeled inventory attributes.

The method proposed in [Eys+12] aims to generate a forest mask (*forested area* label only) using low density airborne lidar. A Canopy Height Model (CHM) with a spatial resolution of 1 m is derived. The positions and heights of single trees are determined from the CHM using a local maximum filter, based on a moving window approach. Only detected positions with a CHM height superior to 3 m are considered. The crown radii are estimated using an empirical function. The three neighboring trees are connected using a Delaunay triangulation applied to the previously-detected tree position.

The crown cover is then calculated using the crown areas of three neighboring trees and the area of their convex hull for each tree triple. The forest mask is derived from the canopy cover values. While this is not a genuine stand delineation method, this approach could be easily extended to a multi-class problem and enlightens the necessity of individual tree extraction even with limited point densities as a basis for the stand-level analysis. A forest stand delineation also based on airborne lidar data is proposed in [Wu+14]. Three features are first directly extracted from the point cloud. A coarse forest stand delineation is then performed on the feature image using the unsupervised Mean-Shift algorithm, in order to obtain undersegmented raw forest stands. A forest mask is then applied to the segmented image in order to retrieve forest and non-forest raw stands. It may create some small isolated areas, iteratively merged to their most similar neighbor until their size is larger than a user-defined threshold in order to product big raw forest stands. They are then refined into finer level using a seeded region growing based on superpixels. The idea is to select several different superpixels in a raw forest stand and merge them. This method provides a coarse-to-fine segmentation with relatively large stands. The process was only applied on a small area of a forest in Finland, thus, general conclusions can not be drawn.

Secondly, several methods fusing various types of remote sensing data have also been developed. The analysis of the lidar and multispectral data is performed at three levels in [TBH04], following a given hierarchical nomenclature of classes in forested environments. The first level represents small objects (single tree scale, individual trees or small groups of trees) that can be differentiated by spectral and structural characteristics using a rule-based classification. The second level corresponds to the stand level. It is built using the same classification process which summarizes forest development phases by referencing to small scale sub-objects at level 1. The third level is generated by merging objects of the same classified forest-development into larger spatial units. The multi-scale analysis offers the advantage of alleviating the standard issue of individual tree crown detection and proposing development stage labels. Nevertheless, the pipeline is highly heuristic, under-exploits lidar data and significant confusion between classes are reported.

The automatic segmentation process of forests in [DKW04] is also supplied with lidar and VHR multispectral images. The idea is to divide the forests into higher and lower sections with lidar. An unsupervised classification process is applied to the two new images. The final stand delineation is achieved by segmenting the classification results with pre-defined thresholds. The segmentation results are improved using morphological operators such as opening and closing, which fill the gaps and holes at a specified extent. This method is efficient if the canopy structure is homogeneous and requires a strong knowledge on the area of interest. Since it is based on height information only, it cannot differentiate two stands of similar height but different species.

In [Lep+08] a stand segmentation technique for a forest composed of *Scots Pine*, *Norway Spruce* and *Hardwood* is defined. A hierarchical segmentation on the Crown Height Model followed by a restricted iterative region growing approach is performed on images composed of rasterized lidar data and Colored Infra-Red images. The process was only applied on a limited area of Finland and prevents from drawing strong conclusions. However, the quantitative analysis carried out by the authors shows that lidar data can help to define statistically meaningful stands (here the criterion was the timber volume) and that multispectral images are inevitable inputs for tree species discrimination.

2.2 Segmentation

The direct segmentation of the optical image and/or the lidar point clouds is not sufficient in order to retrieve forest stands. However, with adapted parameters, segmentations algorithms might be useful to obtain relevant over-segmentation of the data [Dec+17]. They can be divide in two categories:

- The pure segmentation methods, in theses methods, a specific attention must be paid to the choice of the parameter in order to obtain a relevant over-segmentation. Such segmentation can be applied on an image or a point cloud. Specific methods have also been developed for the segmentation of lidar point cloud.

- The superpixels segmentation methods, they natively produce an over-segmentation of the image. The parameters control the size and the shape of the resulting segments.

2.2.1 Traditional segmentation methods

The segmentation of an image can be performed using number of techniques [PP93].
The easiest way to segment an image is the thresholding of a gray level histogram of the image [TFJ89]. When the image is noisy or the background is uneven and illumination is poor, such thresholding might be not sufficient. Thus, adaptive thresholding methods have been developed [YB89].

The segmentation can be considered as an unsupervised classification problem. Algorithms dealing with such problems use iterative process. The most popular algorithm is the k-means algorithm. Segmentation methods using the spatial interaction models like Markov Random Field (CRF) [HE82] or Gibbs Random Field (GRF) [DE87]. Neural networks are also interesting for image segmentation [GPP91] as they take into account the contextual information.

Lastly, the segmentation of an image can be obtained by the detection of the edges of the image [PM82]. The idea is to extract points of significant changes in depth values. Edges are local features and are determined based on local information.

2.2.2 Segmentation of point cloud

The segmentation of point cloud has been highly assessed [NL13]. The aim is to extract meaningful objects. Such extraction has two principal objectives:

- Objects are detected so as to ease or strengthen subsequent classification task. A precise extraction is not mandatory since the labels would be refined after.
- Objects are precisely delineated in order to derive features from these objects. A high spatial resolution is therefore expected.

In forested areas, the only reliable objects to extract are trees. The first way to extract trees from lidar data is to rasterize the point cloud and use image-based segmentation techniques to obtain trees. Several methods have been developed for single tree delineation [Dal+14; Vég+14; Kan+14].

2.2.3 Superpixels methods

Several superpixels algorithms have been developed [Ach+12]. They group pixels into perceptually meaningful atomic regions. Many traditional segmentation algorithms have been employed with more or less success to generate superpixels [SM00; FH04; CM02; VS08; VS91]. These algorithms produce satisfactory results, however, they may be relatively slow and the number, size and shape of the superpixels might not be specified.

Superpixels algorithms have then been developed. One can control the number of superpixel, their size and their shape. [Moo+08] creates superpixels based on a grid. Optimal path are found using graph cut methods. [VBM10] proposes a generation of superpixels based on a global optimization. They are obtained by stitching together overlapping image patches such that each pixel belongs to only one of the overlapping regions. [Lev+09] generate superpixels by a dilatation of a set of seed locations using level-set geometric flow. Resulting superpixels are constrained to have uniform size, compactness, and boundary adherence. Finally, [Ach+12] proposes a generation of superpixels based on the k-means algorithms. A weighted distance that combines color and spatial proximity is introduced in order to control the size and the compactness of the superpixels.

2.3 Classification

A classification is a process that aim to categorize observation. The idea is to assign an observation to one or more classes. This can be done manually or algorithmically. The classification can be unsupervised, the classes need to be learned and the observation assigned. Such classification is similar to segmentation (see section 2.2). The classification can be supervised, the target classes are known and observations with labels are available.

2.3.1 Supervised classification

2.3.2 Feature selection

2.4 Smoothing methods

2.4.1 Local methods

2.4.2 Global methods

3 Method

3.1 General flowchart

With respect to the methods mentioned above, it appears that there are no forest stand segmentation method, based on tree species, that can satisfactorily handle a large number of classes (>5). The proposed framework is a fully automatic and modular method for species-based forest stand segmentation. The method is composed of four main steps; over-segmentation feature computation, vegetation type (mainly tree species) classification and regularization (see Figure 3.1).
Features are first derived at the pixel and at the object level. The most relevant ones are subsequently selected in a supervised way. The objects are extracted using various segmentation methods, since they appear to be sufficient for subsequent steps. A classification is performed at the object level as it significantly improves the discrimination results (about 10% better than the pixel-based approach). This classification is then smoothed. The smoothing may produce homogeneous vegetation type (mainly tree species) areas with smooth borders. The contributions of this method are two-fold:

- Such framework can be fed with specific constraints allowing to tailor the results to specific criteria (height, age, specie, maturity, density, . . .).
- Here, the training set is automatically derived from an existing forest land-cover geodatabase. Specific attention is paid to the extraction of the most relevant training pixels, which is highly challenging with outdated and generalized vector databases.

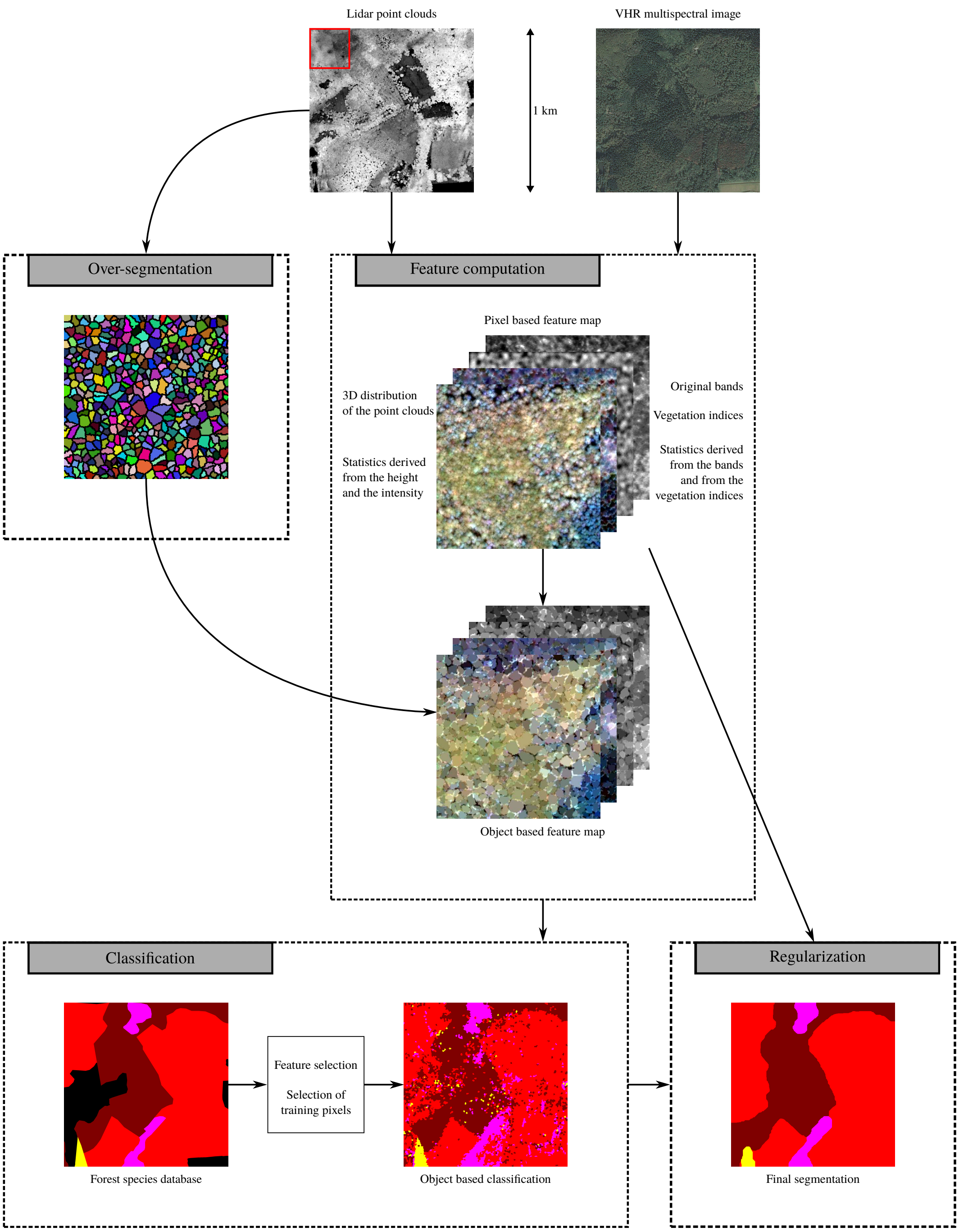

FIGURE 3.1: Flowchart of the proposed method.

3.2 Over-segmentation

3.2.1 Lidar-based methods

3.2.2 Image-based methods

3.3 Feature extraction

3.4 Classification

3.4.1 Training set design

3.4.2 Feature selection

3.4.3 Classification

3.5 Smoothing

3.5.1 Local methods

3.5.2 Global methods

4

Results

5

Conclusion and perspectives

A

Color code

- *Chênes décidus*
- *Chênes sempervirents*
- *Hêtre*
- *Châtaignier*
- *Robinier*
- *Autre feuillu pur*
- *Pin maritime*
- *Pin sylvestre*
- *Pin laricio ou pin noir*
- *Pin d'Alep*
- *Pin à crochet ou pin cembro*
- *Autre pin pur*
- *Sapin ou épicéa*
- *Mélèze*
- *Douglas*
- *Autre conifère pur autre que pin*
- *Lande ligneuse*
- *Formation herbacée*
- *Peupleraie*

TABLE A.1: Vegetation type color code

B Publication

B.1 Journal articles

C. Dechesne, C. Mallet, A. Le Bris, V. Gouet-Brunet. *Semantic segmentation of forest stands of pure species combining airborne lidar data and very high resolution multispectral imagery*. ISPRS Journal of Photogrammetry and Remote Sensing, 126 (2017), pp.129–145, 2017.

M. Fauvel, C. Dechesne, A. Zullo, F. Ferraty. *Fast forward feature selection of hyperspectral images for classification with gaussian mixture models*. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8(6), pp. 2824-2831, 2015.

B.2 Peer-reviewed conference paper

C. Dechesne, C. Mallet, A. Le Bris, V. Gouet-Brunet. *How to combine LIDAR and very high resolution multispectral images for forest stand segmentation?* Proc. of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Fort Worth, USA, July 2017.

C. Dechesne, C. Mallet, A. Le Bris, V. Gouet-Brunet. *Semantic segmentation of forest stands of pure specie as a global optimisation problem*. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2017.

C. Dechesne, C. Mallet, A. Le Bris, V. Gouet-Brunet. *Segmentation sémantique de données de télédétection multimodale : application aux peuplements forestiers*. ORASIS, Colleville-sur-Mer, France, Juin 2017.

C. Dechesne, C. Mallet, A. Le Bris, V. Gouet-Brunet, A. Hervieu. *Forest stand segmentation using airborne Lidar data and very high resolution multispectral imagery*. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 41 (B3), pp 207-214 , ISPRS Congress, Prague, Juillet 2016.

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