Semi-automatic Use of High Resolution Images and Digital Elevation Models for Counting and Identification of Forest Trees

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1. Introduction

This paper presents a semi-automatic and systematic computational approach intending to count and localize different species of trees in zones of dense forest. Comparative analysis of the application of multi-spectral high resolution images and aerial LIDAR data are presented. A method of image segmentation (object-oriented) and a combination of the digital elevation model (DEM) of the crown trees with the reflectance values of the three visible (RGB) and near infrared (NIR) bands of the aerial image are used.

In this field of study Hyypa *et al.* [2004] described different existing algorithms and Suarez *et al.* [2005] presented an efficient methodology to implement a forest inventory by fusing of aerial LIDAR data and digitized aerial photos.

2. Used area of study and available data

For this study, two areas of the forest belonging to the region of Neuchâtel (Switzerland) are considered (Figure 1). This is a zone of dense forest whose main function is to stop possible avalanches.

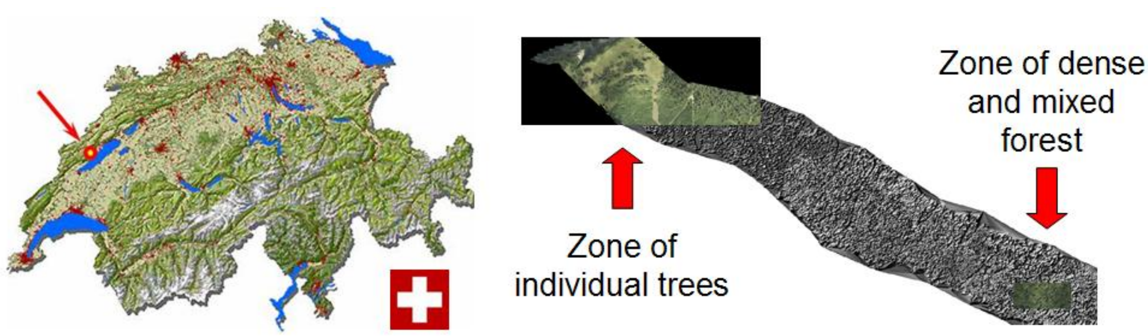


Figure 1. Used area of study

The high resolution images were gotten with a multi-spectral digital camera (*DCM 2001*) and the aerial LIDAR data were processed with a Riegel LMS-Q240i-60 system. The classification of the LIDAR data in field points and non-field points is made with the software *TerraSolid*. The classification and filtering algorithm used by this software is described by Axelsson [1999]. Hence, using all the LIDAR points and only the land points, are interpolated, respectively, a Digital Surface Model (DSM) and a Digital Terrain Model (DTM). The DEM is given by the difference between the DSM and the DTM. The main characteristics of the acquired data are summarized in Table 1.

Data	Resolution		
	Spatial	Radiometric	Spectral
LIDAR	4-6 pt/m2		
Image Visible Channel: RGB	10 cm	12 bits	Bleu: 430-470 Green: 535-585 Red: 610-660
Image: NIR	10 cm	12 bits	Green: 500-650 Red: 590-675 NIR: 675-850
DSM	50cm		

Table 1. Main characteristics of the acquired data

3. Methodology

To fulfill the objectives of this study an object-oriented classification is used. The existing data is treated in two distinct parts. In a first phase, an image analysis with statistical parameters (histogram, maximum and minimum) is processed. In a second phase, an object-oriented classification appealing to a segmentation methodology to count the existing trees is implemented. This technique allows to distingue the two species (leafy or conifer) of existing trees.

Concerning the DEM proceeding from LIDAR data, the segmentation process creates four images relative to the:

1. Elevation of the objects (original DEM and Gaussian filtered DEM: smoothed image using a window of 3x3);
2. Declivity and average curvature of the smoothed image (resultant of point 1) corresponding, respectively, to its first and second derivatives.

This technique has as purpose the creation of homogeneous zones in the top of the trees, because in these zones the first derivatives of altitude are near zero. This characteristic makes the segmentation sensible in these regions, allowing the creation of objects. The average curvature is used with the same objective, creating homogeneous zones considering the concavity of a specific region. Hence, the surface represents a crown tree when the concavity is turned down. Thus, as around the maximum of the function, corresponding to the top of the tree, the curvature will have a homogeneous behavior, the segmentation will allow to easily identifying these same zones.

After the segmentation of the different images, a counting of trees and validation of results are proceeded. This validation is made through a photo interpretation in a GIS environment, using 4 zones of test delineated under the used visible image.

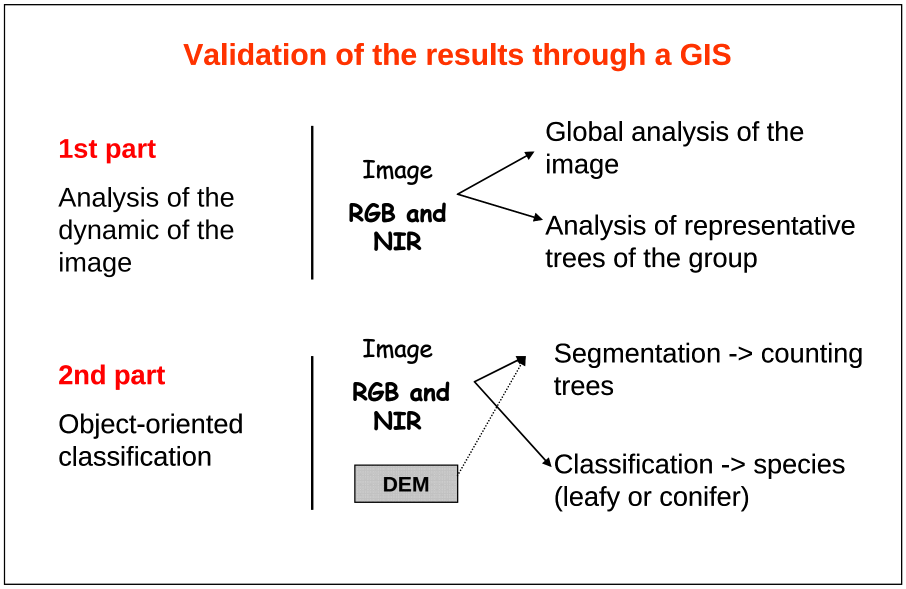


Figure 2. Validation of the results through a GIS

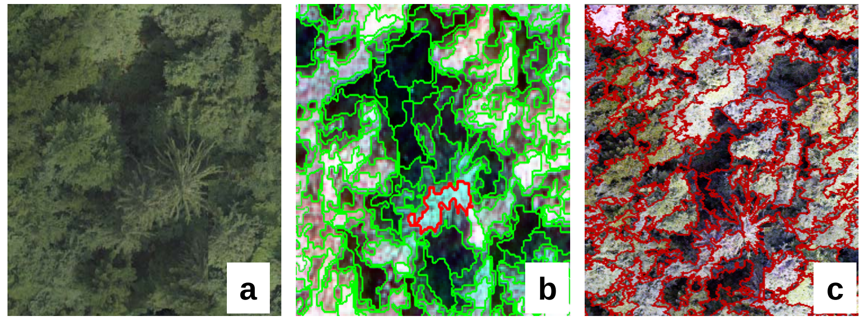
4. Presentation of results

One single result is calculated using an object-oriented classification (implemented with the software *eCognition*) and based on the statistical analysis previously made.
Additionally, six different results corresponding to the segmentation of the RGB, NIR, DEM, DEM filtered, derivative of the DEM filtered and average curvature of the DEM filtered bands are calculated.

4.1. Segmentation

The Figure 3 shows an extract of the segmentation's results carried trough for one given zone. In this extract, three contiguous conifer trees (positioned in the centre of the image), shadow zones and several leafy trees can be observed. The scale values (Sc.), color (Col.) and compacity (Com.) used on the segmentation are presented in the existing table of the left top corner of this same Figure 3.

	Sc.	Col.	Com.
Image VC	40	0.9	0.5
Image NIR	15	0.9	0.5
Not filtered DEM	5	0.9	0.5
Filtered DEM	4	0.3	0.7
Declivity Filtered DEM	10	0.1	0.9
Avg. Curv Filtered DEM	5	0.3	0.7



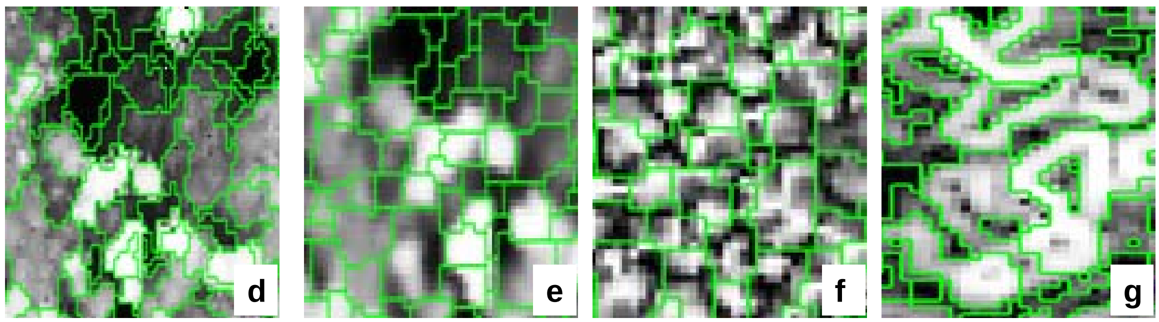


Figure 3 – Results of the segmentation using different sets of image's data: table with the used values on the segmentation; a) image of the studied zone b) RGB visible bands segmentation; c) NIR band segmentation; d) DEM segmentation; e) filtered DEM segmentation; f) declivity of the filtered DEM segmentation; g) average curvature of the filtered DEM segmentation

On the three visible bands' image segmentation, the noise caused by the existing shadows doesn't allow to correctly explore its spectral signature. Moreover the homogeneity of the green tones of the forest cover makes it also difficult.

The DEM without filter presents an insufficient segmentation due to the existing noise of the image, possibly caused by the high resolution of the altimetry LIDAR data used. When comparing the not filtered DEM with the smoothed filtered DEM it can be verified that the segmentation is much more efficient for the second case.

Thus, on the visible image are randomly chosen four test zones. For each one of these four zones, the resulting polygons of the different segmentations are reduced to its mass center, allowing the representation of each tree by a single point. Later, using a photo-interpretation technique, the top of each tree is also represented by a single point, making possible a visual validation of the results inherent to each one of the different segmentations. Due to the bad results of the visible image its results are not validated. The obtained results after the segmentation process can be consulted on Table 2.

	Zone 1	Zone 2	Zone 3	Zone 4
Existing trees (manually counted)	19	29	19	23
NIR	130	135	94	107
Not filtered DEM	56	52	41	39
Filtered DEM	42	36	35	32
Derivative of the filtered DEM	68	71	41	51
Average Curvature of the filtered DEM	16	28	17	16

Table 2. Obtained results after the segmentation process

4.2. Classification

The classification process, using an object-oriented approach implemented by the software *eCognition*, is based on the local statistical analysis (tree level) previously made to the high resolution images. This allows comparing the different histograms concerning the images. The visible image's histograms analysis confirms that the species are not distinguished in the visible spectrum, mainly due to the great homogeneity of existing information of the visible band. However, as showed in Figure 4, the NIR band data clearly presents two level signatures for each one of the two represented classes: leafy and conifer. Hence, will be defined two spectral signatures (belonging values) in order to classify these two species of trees thereafter.

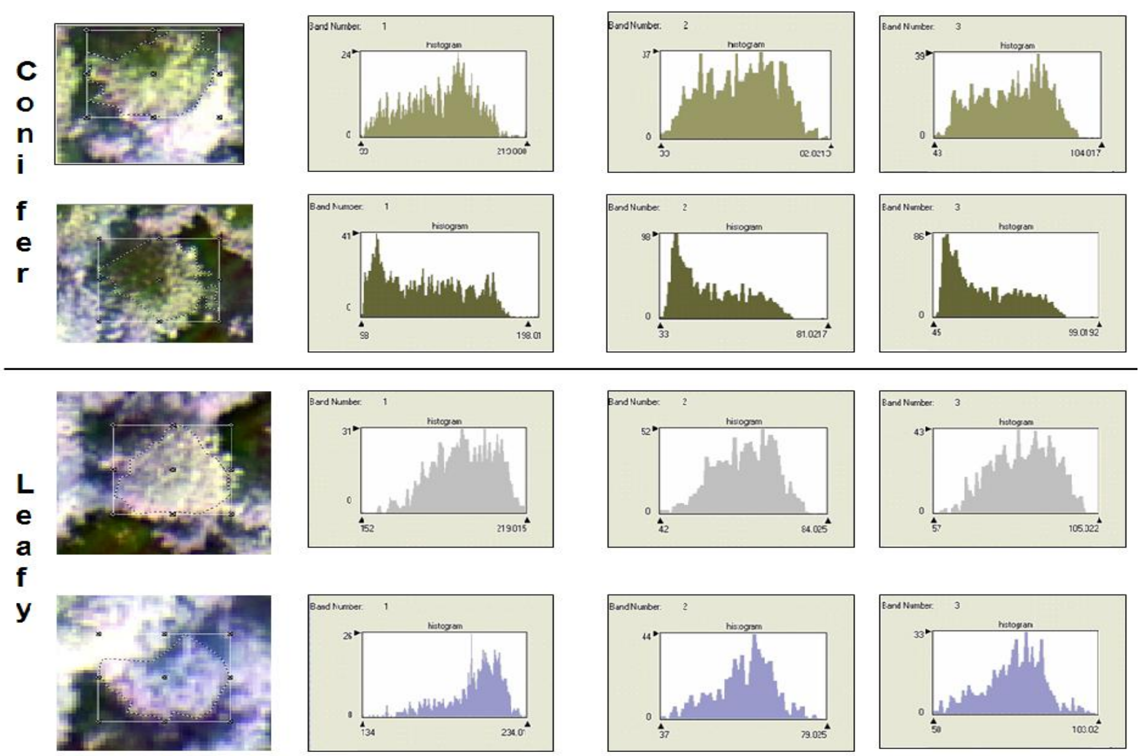


Figure 4. Local statistical analysis of two different trees (for each of the two existing species) in the NIR band data and its respective histograms

Thus, based on the segmentation of the infrared image and introducing the values belonging to each of the two existing species, two classes are then created: leafy and conifer. A third class relative to shadow's zones with absence of reflectance is also considered (Figure 5).

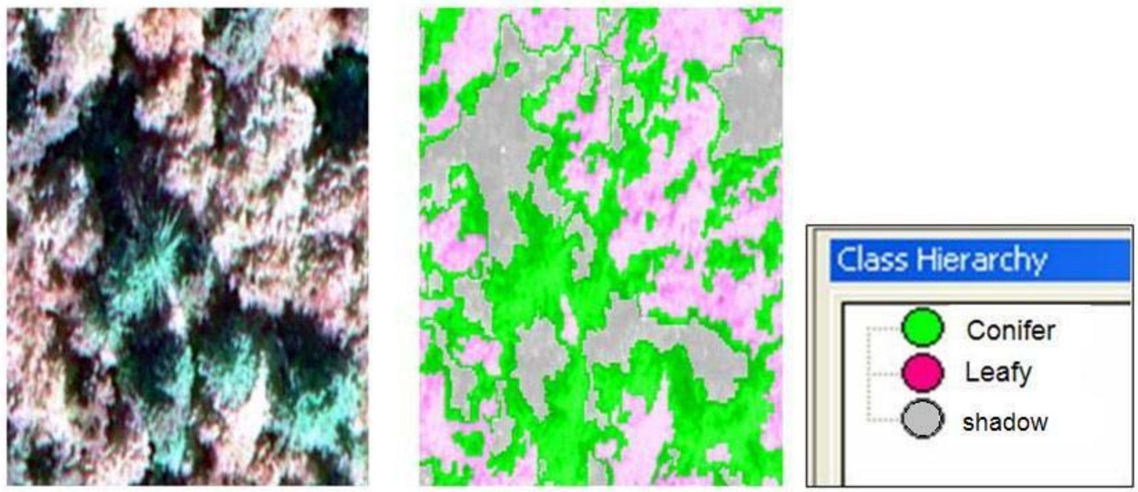


Figure 5. NIR image: final object-oriented classification implemented (test zone 1)

These results are validated according to the same parameters used in the validation of the segmentation's results. The Table 3 shows the results given by the classification of the existing classes in the NIR band data.

	Zone 1		Zone 2		Zone 3		Zone 4	
	Con.	Leaf.	Con.	Leaf.	Con.	Leaf.	Con.	Leaf.
Trees counted manually	5	14	23	6	9	10	16	7
Evaluation of the classification on the NIR band	5	13	23	6	9	9	16	5

Table 3. Obtained results (four different zones) after the classification process (NIR band data) of the conifers (Con.) and leafy (Leaf.) trees' species

5. Conclusion

The counting of trees in dense forest zones using the visible and infrared bands showed to be inefficient. However, the average curvature of the filtered DEM is an acceptable methodology given that the curvature values are very close to the reference values.

The classification of the existing species (leafy and conifer) using the visible bands proved not to be efficient to detect the spectrum signatures. Despite this, the species' classification using the infrared band showed to be extremely satisfactory. In this case, the few misidentifying directly result from the discriminating capacity of evaluation of one class when compared to the other.

The proposed analysis presents a new vision relative to the study of forest management. Several future developments can be considered, such as:

1. Coupling of NIR image with the digital models derivate from aerial LIDAR data, by taking into account the problems of projection of each type of data;
2. Applicability and usability of the proposed methodology to other types of vegetation.

Finally, it could be interesting to compare the results gotten in this work with the results manually counted by the forest-guards.

6. References

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