Neural network and quad-tree approach to extract tree position and height from LiDAR data

Francesco Pirotti[1], Alberto Guarnieri[2], Antonio Vettore[2]

[1] Department of Land and Agroforestry Systems, University of Padua, viale dell'Università 16, 35020 Legnaro Italy – francesco.pirotti@unipd.it
[2]CIRGEO, Research Center for Geomatics, University of Padua, viale dell'Università 16, 35020 Legnaro Italy – cirgeo@unipd.it

Abstract

This paper reports an analysis of results from processing return signals from canopy covers using a artificial neural network to find if there is an improvement on detecting tree height and position compared to a more classic local maximum filter approach. The hypothesis taken into consideration is that a neural network permits to insert several useful parameters in the decision process thus making it more “programmable” and apt be used in different forest cover situations. Quad-tree is a method to organize the data to optimize the process done by the neural network.
We conclude that results from classic methods and the neural network both give significant results compared to ground-truth measured on the terrain. If the network is implemented with a certain number of trainers there is an improvement compared to the local maximum, but the difference is not statistically significant. Nevertheless further improvements can be foreseen in the future thanks to the intrinsic nature of neural networks to be able to include additional nodes to adapt itself to the final objective – tree recognition.

Keywords: neural network, local maximum filter, LiDAR

1. Introduction

New LiDAR technology has opened new frontiers in many fields which benefit from geomatic information. LiDAR surveys give three-dimensional spatial data with significant accuracy and also integrate other information such as intensity of return signal, metric and non-metric images as well as hyperspectral images to give end-users remotely sensed information which can be, to a certain degree, correlated to stand characteristics.

Forestry and related environmental sciences have been looking into LiDAR for accurate spatial modeling of trees and terrain. Land use mapping is of primary interest in land planning and LiDAR has proven a significant added value to classic remote sensing image classification methods (Lee and Shan, 2003).

In the field of forestry, future research is focused on LiDAR-processing methods which will permit to extract information at lower costs. Classic methods require forest characteristics to be assessed using ground-plots, field-data and statistical methods. Error sources and factors to consider in field methods are the reliability of the workers (human error), statistical method adopted (number of samples, variance, significance of the test) and costs.

LiDAR data and higher training of operators able to process remote sensing data correctly, will pay back in lower costs and higher accuracy for forest inventories. Of course remote sensing will never replace completely field work because ground truth and on-site experience are very important factors, but a lot of tedious and repeating forestry work can be substituted with state of the art LiDAR data processing.

Tree species, mean diameter and height distribution in the stand are all information which are used in forest planning and inventories. This information can be correlated with LiDAR data with a certain amount of reliability. Tree top extraction from LiDAR data gives 80% accuracy in uneven stands, better than digital photogrammetry and comparable if not better than ground measurements (Koukoulas and Blackburn 2005; Stonge *et al.,* 2004; Magnussen *et al.*, 1999). Integration of LiDAR with remote sensing imagery (Bork *et al.* 2007) is also promising because of complementarity between the two types of data, one giving geometric information the other spectral information.

2. Methods

The process was applied to a small test site to check for accuracy of results by comparing with ground-measured truth.

2.1 Study area

Figure 1: Study area

The whole study area comprises of a watershed basin located in the Belluno province, in the Veneto Region in Italy. This area was chosen because it presents an interesting combination of orographic and vegetation characteristics. Steep slopes and flat ground are present, as well as bare soil/rock, grassland and four different tree-species. Height above sea level variation goes from a minimum of 1120 m to 2600 m. The stream-line follows an almost east → west direction as can be seen from figure 1 which is oriented north. Length of its major and minor axis are respectively 3125 and 2200 meters.

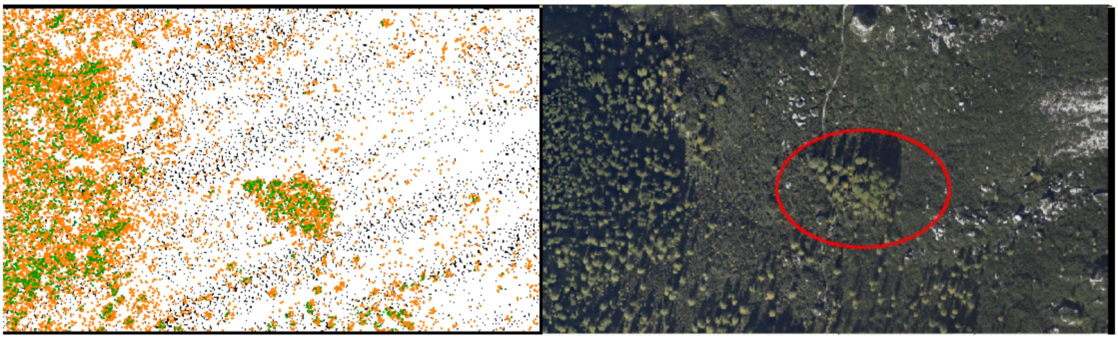

Figure 2: Sub-area used in analysis; left from laser points, right from RGB image

LiDAR and image data were recorded at the same time during a flight which took place the 13th of July around 14:00 italian time. High resolution orthorectified images of the area at a mean spatial resolution of 15 cm were therefore available. Cloud of LiDAR points has a density of 6-11 pts / m^2 where a single signal return was detected. Density can get as high as 19 pts / m^2 where vegetation causes multiple returns.

Around 35% of the study area is covered by bare ground, and the rest is mostly covered by forest with a limited presence of grassland. Tree species present are: *Larix decidua, Picea abies, Pinus mugo* and *Fagus sylvatica*. Some salix is present at the lowest points of the basin, but not in significant numbers. There is a vast majority of *Larix decidua* and *Picea abies* which corresponds to Del Favero's classification of forest typologies (Del Favero 2004).

2.2 Dataset

For this particular analysis a sub-area was chosen with a total of 6000 m^2 and with 55750 points. The first step was to isolate the points belonging to the sub-area and to gather all information on ground truth. Tree breast height diameter (BHD) and tree height were recorded by a survey while geographic position was recorded using the high resolution image. Ground measures and the digital orthophoto were used to digitize canopy borders as well.
The first processing step was to correct absolute height values of points by subtracting the

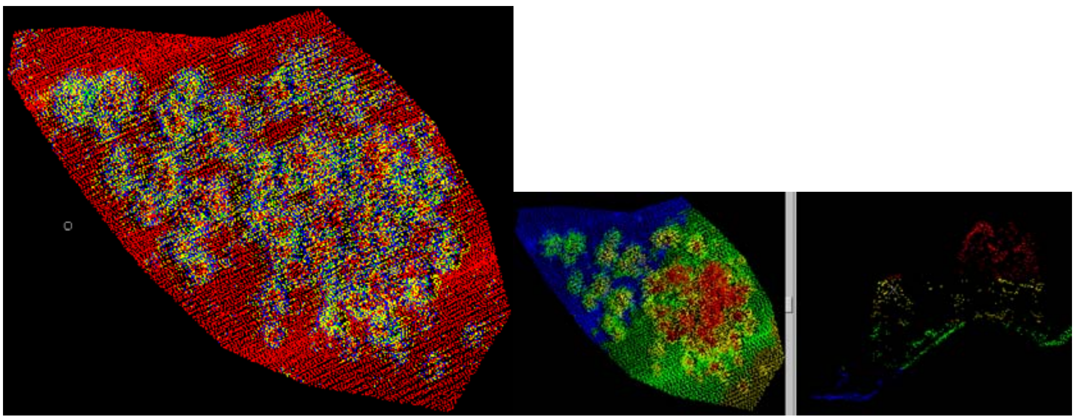

Figure 3: Sub-area for study: left – class by echo, middle – class by height, right right a section showing ground irregularity and canopy models.

ground model creating a new variable called *dz* which represents the height above ground of each point. The minimum threshold for points to consider was 0.5 m above the ground to filter out most understory vegetation. After this process the *dz* variable had a maximum value of 29.32 m, which is reasonably close to that of the highest tree which is 29.81 m. LiDAR measure of tree height have an error which can be estimated from its components. First of all the error from the laser sensor: ± 0.3 m as reported by constructor. Then the highest point is not necessarily the actual tree top and since point density is about 6-11 pts / m^2 that would mean 0.2-0.3 m between points, therefore 0.1-0.15 m in the worst case scenario. The total is 0.45 m difference between points, which can be considered the same height-wise if canopy has a slope of one.

The LiDAR data in the sub-area was furthered filtered out in order to isolate a dataset with unique echo plus first-of-many echo (UFE). The points from the UFE set where included only if they did not belong to ground class (see equation 1).

This set gives us points which belong to vegetation, but without intermediate or last echoes, but only with unique echo and first-of-many echo. This is actually a subset of the previous dataset where intermediate and last echoes are removed thus giving us the position in space of the first surface which caused the return of the laser signal towards the sensor. The total number of points for this dataset was 20253.

$$\text{UFE} = \text{Unique} \cup \text{first-of-many} \cap \text{ground class} \quad (1)$$

This set gives us point population which represents the canopy model surface.

LiDAR data was processed with commercial software Terrascan from Terrasolid © , the neural network process was costum designed with a dynamic linked library developed in C language. The dataset was pre-processed with a low-pass filter correctly scaled to smooth out the noise due to leaf-scale variability.

2.3 Neural Network and quad-tree setup

The model for decision process is a back-propagation artificial neural network (ANN), while the organization in a quad-tree structure is integrated in the neural network. The structure of both the ANN and the quad-tree was setup using C code, compiled both as a library and as a stand-alone executable. The process reads the data, organizes points into quad-tree bins, sends data to the ANN, and receives feedback from the ANN for training.

2.3.1 Quad-tree organization

Data is fed to the first function as a table with these columns: x,y,dz,echo number and echo type. The spatial domain falls in the first three columns, whereas the others are added alphanumeric information. The spatial data will be processed contextually, furthermore topological relations such as nearest neighbour and focal statistics are important as they can give added criteria to the process. That is the reason why the data was organized into a quad-tree which assigns points to a certain address in the tree. In this case each "leaf" in the quad-tree is cannot have more than 9 points and less than 4 points. Spatially this means that each smallest square covers about half of a squared meter.

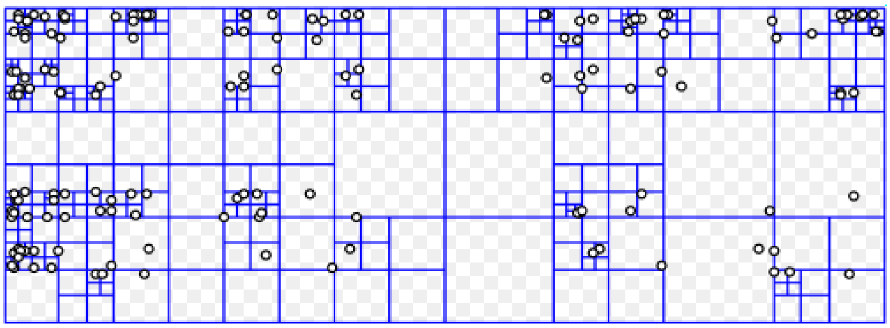

Figure 4: Example of quadtree organization

2.3.2 Neural network: nodes and neurons

The points are fed to the ANN, which evaluates criteria, assigns weights and defines if a point is part of tree-top or it is part of canopy and if it part of canopy borderline.

Criterion for assigning a point to the tree-top class and parameters which can be tuned in the ANN and therefore make up the hidden nodes:

1. Point is a local maximum considering a certain radius. Radius will actually be a multiple of the spatial resolution of the smallest "leaf" of quad-tree and is a parameters which can change to tune the ANN.
2. Point must have neighbors with a local density totaling at least the minimum point density divided by two around an area which is dependent on tree species and configuration. The area to consider is also a parameter which can vary.
3. To be considered actual top of the tree a point must coincide with topmost value of local kriging interpolation, if it does not then a new point is created with such coordinates.
4.

A variable number of points are used as trainers for the ANN, as backward propagation permits to calibrate parameters in the hidden nodes in order to improve accuracy at each iteration of the process.

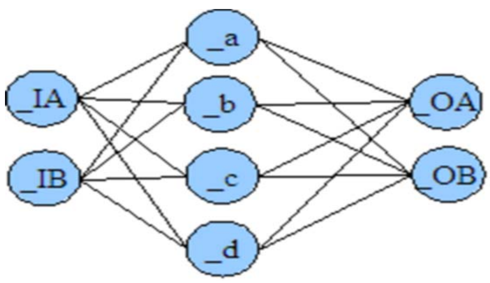

Figure 5: Neural Network: _I*n* = input nodes, _*n* = hidden nodes, _O*n* = output nodes

The actual tree top is determined after using a kriging interpolator of the point itself and 18 nearest neighbors. The interpolation part was done by having a call to a separate module from GRASS open source software, as it would have been a hardous and time consuming task to implement a kriging interpolator directly in the C library.

3. Results

Encouraging results were found even if not significantly different from classic local maximum filters. The number of trainers previously set in the output layer is important, as will be discussed in the next section.

Table 1: Results from ANN using different number of training outputs

Thinning operation	Number of trees correct	Number of trees incorrect*	Total trees found	RMSE of positioning (cm)
Ground - truth	*56*	*na*	*56*	*na*
Neural network with 2 trainers	44	8	52	24
Neural network with 4 trainers	41	9	50	24
Neural network with 8 trainers	55	4	59	21
Neural network with 14 trainers	59	2	61	23
Neural network with 20 trainers	55	8	63	23
Local maximum filter	52	4	56	24

*Defined as not belonging to tree top but to canopy

4. Discussion and conclusions

The results seem promising even if not significantly different from the local maximum filter. If the network is implemented with a certain number of trainers there is an improvement compared to the local maximum, but the difference is not statistically significant. Nevertheless further improvements can be foreseen in the future thanks to the intrinsic nature of neural networks to be able to include additional nodes to adapt itself to the final objective – tree recognition.

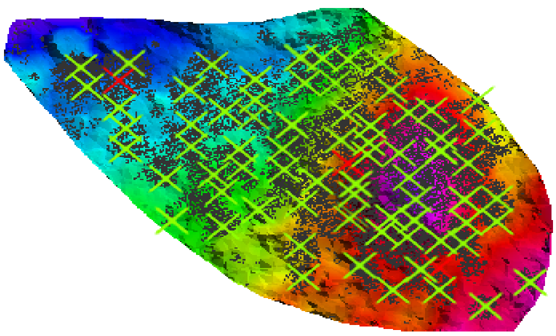

Figure 6: Point distribution on top of ground digital elevation model – green crosses represent trees found with 14 trainees while red crosses indicate misinterpretations.

Some drawbacks to this method are found in the complexity of its actual implementation by untrained professionals. Normalization of data, initial tuning of parameters and preprocessing of data should by done accurately, and it is often a source of error which heavily weights on final result.

There is a lot of testing and refinement to be done to this method. It will be an interesting phase in the future to measure other datasets in the Missiaga basin to find if forest types can be associated with weights and parameters which make up the trained ANN.

References

Ananth U. Kini, Sorin C. Popescu, 2004. TreeVaw: a Versatile Tool for Analyizing Forest Canopy LiDAR Data – a Preview with an Eye towards the future. ASPRS Images to Decision: Remote Sensing Foundation for GIS Applications September 12-16, 2004

Bork E. W., Su J. G. 2007. Integrating LIDAR data and multispectral imagery for enhanced classification of rangeland vegetation: A meta analysis Remote Sensing of Environment, 111, 11-24.

Del Favero R. (2006), Carta regionale dei tipi forestali: documento base, Regione Veneto.

Koukoulas, S., & Blackburn, G. A. 2005. Mapping individual tree location, height and species in broadleaved deciduous forest using airborne LIDAR and multi-spectral remotely sensed data. International Journal of Remote Sensing, 26, 431-455.

Lee, D. S., & Shan, J. 2003. Combining LIDAR elevation data and IKONOS multispectral imagery for coastal classification mapping. Marine Geodesy, 26, 117-127.

Magnussen, E., Eggermont, P., & LaRiccia, V. N. 1999. Recovering tree heights from airborne laser scanner data. Forest Science, 45, 407-422.

Stonge, B., Jumelet, J., Cobello, M., & Véga, C. 2004. Measuring individual tree height using a combination of stereophotogrammetry and lidar. Canadian Journal of Forest Research, 34, 2122-2130.