TREE CROWN DELINEATION FROM DIGITAL ELEVATION MODELS AND HIGH RESOLUTION IMAGERY

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ABSTRACT :

The aim of this study was to develop a methodology to delineate accurately tree crowns using digital elevation models independently of source (laser scanned data or stereoscopic pairs) and to identify the complementary information that can be obtained from high resolution imagery. This methodology uses the Watershed algorithm as the baseline. However the direct application of this algorithm generates over-segmentation for complex tree-crowns and non-wooded areas. To solve these problems a preprocessing stage consisting of a mixture modeling adaptive thresholding technique was developed to remove non-wooded areas. Results obtained on different plots of land are discussed putting forward the influential factors.

1. INTRODUCTION

There is an increasing need for accurate and cost effective forest resource information for operational and strategic applications (ecological sustainability, forest exploitation, rural development). The combination of high resolution digital elevation models, obtained for example from laser scanned data, and multispectral images appears particularly promising as a source of forest survey tools (Leckie *et al.*, 2003).

Research in the area of high resolution imagery (HRI) has led to the development of several methods for tree crown delineation. Tree tops often appear as maxima in intensity in satellite pictures and cast shadows around the tree crowns. In a 3D model where height corresponds to spectral intensity, tree crowns can be seen as peaks and shadows as valleys. Gougeon (Gougeon, 1998) developed a tree crown delineation method using these properties with a valley following approach. A similar technique was used by (Warner *et al.*, 1998) but this time using texture to allow the detection of trees with a lower intensity. The results are generally good in high to medium density conifer forests. Preprocessing to remove non-vegetated areas is necessary for lower density areas.

Methods that use region approaches have also been studied (Brandtberg & Walter, 1998; Culvenor *et al.*, 1998). The zero-crossings of the second derivative (Laplace operator) can be used to detect parts of the tree crowns. A region growing algorithm can then be used with the tree tops (maxima spectral response) as seeds and light intensity as growing function right up to the pre-calculated boundaries. These methods are more robust for detecting trees which are partly in shadow. However preprocessing is also needed to avoid detecting light patches in lower density areas. Pollock (Pollock, 1998) uses model matching, training and spatial information to locate tree crowns. The advantage of this type of approach is that it avoids improbable regions. However in Pollock's method, the training is performed by an operator. This could be a disadvantage in some circumstances. Voronoï diagrams with a fuzzy approach have also been tested (Dubé *et al.*, 1998). The use of a probabilistic model is also an efficient way to avoid unlikely regions. Research in the field of high resolution radar sensors is recent. At first these were used as an efficient way to generate digital terrain models (DTM) for orthorectification of digital satellite imagery. Later they were used to study tree heights (Andersen *et al.*, 2001) and to identify trees by using the pulse response of the vegetation (Pyysalo & Hyyppä, 2001). Numerous studies have confirmed the importance of small footprint LiDAR data for forest inventories. Stand characteristics, like tree heights, basal area and stand volume can be accurately estimated by using laser scanning (Maltamo *et al.* (2004); Naesset & Bjerknes (2001); Means *et al.* (2000)). Some countries are considering in a close future the use of LiDAR technologies to perform their forest inventories (Nilsson *et al.*, 2003; Wulder, 2003).

Digital elevation models (DEM) obtained by LiDAR sensors or stereoscopic views have more rarely been used for tree delineation. The chief advantage of DEMs is that they are not affected by non-uniform light intensity. This means that they can be used to detect trees that would otherwise be in shadow. Obtaining tree heights is also an interesting characteristic. However DEMs are often less precise than HRI and trees that are very close cannot be extracted.

The aim of the work described in this article is to use the complementary information from both a DEM and HRI of the same region to obtain a robust tree crown delineation algorithm. Although the DEMs employed in this study have been obtained from LiDAR data and consequently DTMs can also be extracted, it has been decided that the approach should be DTM independent in order to be able to use DEMs obtained from stereoscopic views.

2. STUDY SITE AND DATA

The study site is a Mediterranean forest located near Montpellier city, in the south of France. In order to identify the limits of the application of the method according to the stands characteristics, six plots dissimilar in dominant species, diameter-class distribution and tree spatial distribution were selected : a closed and an open mature

Aleppo pine (Pinus halepensis) stand, an umbrella pine (Pinus pinea) young plantation, a mature poplar plantation and an olive orchard.

The data used in this study consists of :

- 1 m resolution digital elevation and terrain models (DEM and DTM) produced by an engineering firm, GeoLas Consulting, from LiDAR data with a 15 cm horizontal precision and a 0.5 m vertical precision. These data were acquired on 26th June 2002 with a small-footprint Toposys laser scanning system.
- orthorectified multispectral images (blue, green, red and Infra Red channels) with a 0.5 m resolution, acquired with a digital line camera that was operated in parallel with the LiDAR instrument. All the data are georeferenced to the RGF 93 coordinate system.

A ground truth database was available for the two Aleppo pine stands and the Umbrella pine plantation. It includes, for each plot, 1) individual tree location recorded in the RGF 93 coordinate system and 2) dendrographic measurements (mean or both south-north and east-west crown diameters; total height, stem height, stem diameter at 1,30 m above ground). For the poplar plantation and the olive orchard, trees were easily identifiable on the IRC images and were manually delineated. The resulting vector layers were considered as the ground reference.

3. METHOD

3.1 The watershed algorithm

DEMs can be represented as grayscale images with the pixel values representing altitude. By inverting the images, trees appear as catchment basins. These provide the right configuration for the application of the Watershed algorithm (Vincent & Soille, 1991).

The results obtained by the direct application of the algorithm on a DEM led to 1) over-segmentation of most of tree crowns and 2) imprecise borders obtained in low tree density areas To overcome this problems a specific methodology was developed (Fig. 1).

3.2 Pre-processing the DEM

The over-segmentation of regions is not due to the classic problem of the nature of the image (which would have led to the application of a distance transform, a geodesic erosion or a marker-controlled segmentation). In this figure the over-segmentation is due to the complex tree crowns which do not conform to the basin assumption. Pre-processing with the application of a median or averaging filter with a mask approaching the actual size of the trees in the image can improve the results, the disadvantage being that some regions are then under-segmented.

3.3 Extracting wooded areas

The second problem to be solved is the imprecise borders obtained for the tree crowns in low density areas. In this case, the Watershed borders do not correspond to tree crowns (Fig. 2).
Separating terrain and non terrain areas (including trees) would solve this problem. Where a DTM is available, vegetated area extraction is possible by thresholding the image difference $DEM - DTM$. This is not possible with the DEM on non flat areas because the altitude of the terrain

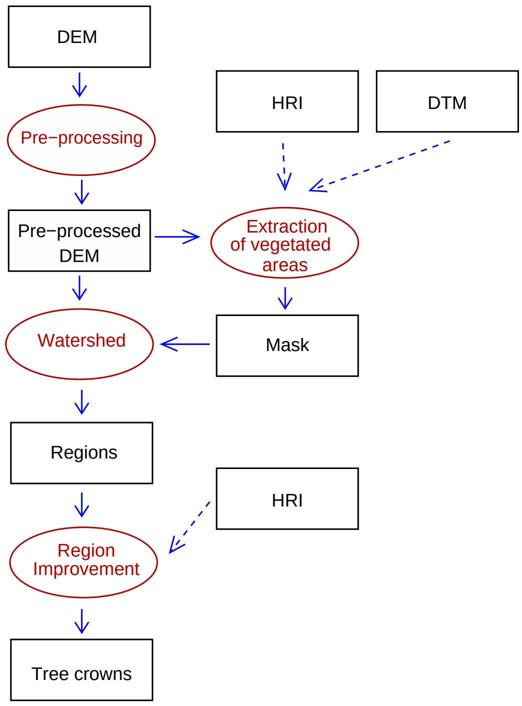

Figure 1: Methodology for tree crown delineation

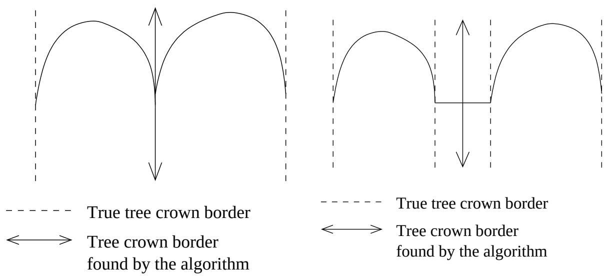

Figure 2: Position of the watershed borders for high density wooded areas (left) and for low density wooded areas (right)

is irregular.

A method has been developed to extract wooded areas from DEMs (it was again decided to use DEMs instead of HRIs to avoid the problem of shadowed trees). The histogram of a DEM on a small vegetated region frequently contains two classes : the first corresponds to ground pixels, the second to tree tops. Spliting the DEM into squares and estimating a threshold elevation value for each square makes it possible to separate the trees from the ground locally (Fig. 3).

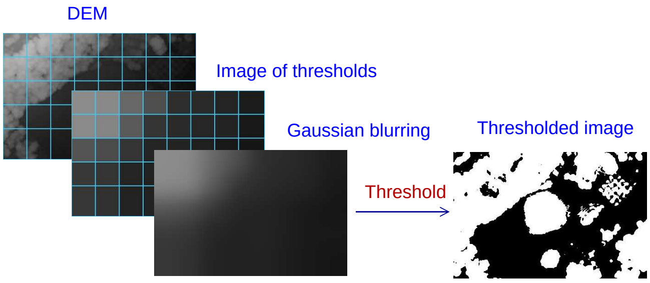

Figure 3: Adaptative thresholding for wooded areas extraction

This procedure is simplistic because some squares may not contain two classes (both ground **and** trees). It is essential to take into consideration the size of squares required to obtain a robust separation of these two regions.

These difficulties have motivated the use of a Gaussian gray-level histogram modelling algorithm where both classes were modelled by a Gaussian that minimized the approximation error (Fig. 4). The threshold is at the intersection of both Gaussian functions. The functions' characteristics can then be used to identify the regions that have been incorrectly thresholded.

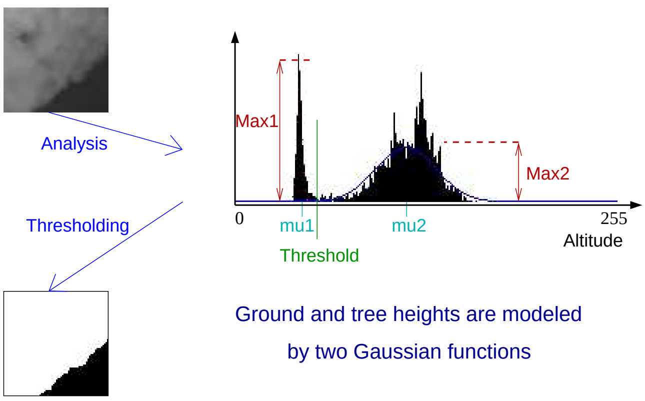

Figure 4: Mixture modelling applied to the histogram

The variables used to identify the incorrectly thresholded regions must be independent of altitude (you can not just compare the thresholds). The following variables were used taking this into consideration :

- $\frac{\max_1}{number\ of\ pixels\ per\ square}$, $\frac{\max_2}{number\ of\ pixels\ per\ square}$
- $\frac{(\max_1 - \max_2)^2}{number\ of\ pixels\ per\ square}$
- $(\mu_1 - \mu_2)^2$
- $\sigma_1,\ \sigma_2$

Incorrectly thresholded regions have been identified by comparing their variables to the Gaussian distribution generated by the variables of all the thresholded regions. This approach can be seen as a way of learning the global distribution of trees over a given region.

A region can be incorrectly thresholded either because it is homogeneous (only trees or only ground) or because the trees are different to those in the rest of the DEM. By increasing the size of the square used for the region, it may be possible to make the region ressemble the surrounding regions more closely and find a satisfactory threshold (Fig. 5).

Figure 5: Result of the adaptive thresholding algorithm before correction (left) and after correction (right)

3.4 Automatic tree delineation

After masking by applying the adaptative threshold, the watershed algorithm is applied. Regions obtained in that way may contain buildings. These non vegetated regions can easily be identified using the normalized difference vegetation index (NDVI) on the HRI.

The higher precision of the HRI can also be used to improve borders of the identified tree crowns.

3.5 Validation

The results of the automatic terrain/non-terrain classifications are compared to a reference classification by analysing the contingency matrices. The reference classification was obtained by thresholding the Canopy Height Model ($CHM = DEM - DTM$). The threshold was set manually so as to best suit the wooded areas visible on the IRC image. Evolution of the classification accuracy with the size of the square that was chosen to split the DEM is analysed for the different stands and related to the stand characteristics. The results were analysed before the iterative improvement step.

The theoretical optimal size of the square used on the DEM image in the terrain/non-terrain separation method can be estimated for a regular stand. The window must contain at least one pixel of each class (terrain/non-terrain) whatever its position. The optimal size of the window is then a function of the tree diameters, distance between trees and direction of the plantation. It varies quite a lot according to the stand characteristics, from $d/2$ to $d\sqrt{2}$ for stands composed of trees at a distance d with perfectly round crowns. For real stands we assumed that the mean distance between trees for open stands, or between gaps for closed stand, could give a rough approximation of the optimal square size. This mean distance was estimated from the density of trees (respectively gaps).

The results of the automatic tree delineation (called segmentation in what follows) are compared to ground reference delineation of trees. The delineation used as the reference were obtained either by photo-interpretation of the IRC images for uniform stands with well individualised trees or using a ground truth data base for the other stands. A statistical analysis is first performed. The number and the size of automatically delineated trees are analysed for each selected plots and compared to the ones of the reference delineation. A more precise analysis, which can be called "the spatial analysis of the segmentation", is performed by comparing the segment boundaries resulting from the automated recognition method to the ground reference. The layers are compared in a vector format. Seven types of overlaps are defined for segmentation accuracy assessment. A tree is well identified when there is a one-to-one correspondence (only one segment associated with one ground delineation and vice versa), with a tolerance of a two pixels gap between both boundaries and with an overlap area greater than 80 % of the delineated tree area. The other classes are : over-segmented trees (more than one segment associated with one ground delineation) ; under-segmented trees (a segment includes significant part (>10 %) of more than one tree); trees that are both "over-segmented" and "under-segmented" that is to say that among the several segments associated with the ground delineation at least one is common to two or more trees; trees that are well identified but with an overlap area <80 % of the delineated tree area ; omitted trees ; and finally segments not associated with a tree (commission errors).

4. RESULTS

4.1 Extraction of wooded land

For five stands (olive orchard, poplar, dense pine stand, sparse pine stand, young pine plantation) the evolution of the classification accuracy with respect to the initial square size for the extraction algorithm is analysed. For olive orchard, a large range of values was studied, from 1 to 40 meters with a one meter step. For other stands the studied size are spaced between 5 and 10 m. The maximum classification rate and the corresponding window size are related in table 1. The classification rate corresponding to the square size which is the closest to the mean distance between gaps or trees is also reported in table 1.

The maximum classification rates are high for all stands (from 87.9 % to 98.7 %). For most of the stands the classification rates obtained with a square size close to the mean distance between trees or gaps stay high except for poplar and young pine plantations. The sharp decrease of the classification accuracy rate (>10 %) for these stands can be explained by the non homogeneous spatial distribution of the gaps (all around the plot for example for the pine plantation). In that case mean distance is no more a good indicator of the optimal window size.

These results show the good potential of the proposed method to separate terrain and non terrain. The adaptive step decreases the sensitivity to the initial size square as expected.

4.2 Tree segmentation

The number of trees of the ground reference data and the automatically delineated per radius classes are shown in Fig. 8. The results of the spatial comparison between the automated recognition method and the ground reference segmentation are presented in table 2. This spatial analysis was only realised for two plots. For heterogeneous stands (closed and open pine stands) the reference vector layers obtained from the ground truth data base did not fit enough the IRC images to be usable (tree crowns approximated with circles, shifts in tree locations).

The best results are obtained for the poplar plantation. Only a slight over-segmentation is noticed (+6 % of the trees). The mean radius of segments is greater than the tree radius (+41 %) and this over estimation is observed for all the radius classes (see the shift in the histograms on fig $). However 80 % of the trees are well identified which indicates that the over-estimation of the radius stays in the limits set for an accurate segmentation. Taking into account the class of "well identified trees with a problem of area" the number of well identified trees reaches 90 %.

For the olive orchard, an homogeneous stand with 71 % of the trees in the same radius class, the results are not as good. We can notice an over estimation of the number of trees obtained by automatic segmentation for all the classes of radius except for the $[2\ m - 3\ m[$ radius class that contains most of the trees. Trees were either over segmented or under segmented. This is finally expressed by a number of segments greater than the real number of trees (+26 %) and by a mean of segment radius approximately the same as the real tree one (0.27 pixels). The well identified trees represents only 52.6 % of the trees (76.3 % if well identified trees with a problem of area are included). This result can be explained by the shape of olive trees. These fruit trees are pruned in their centre in order to let the light get into the middle of the trees. The crown shape has no more the appearance of a catchment basin on the inverted DEM but is closer to a *torus* which explains the over-segmentation and misplacement.

For the two last stands analysed, the open pine stand and the closed pine stand, most of the trees have a small diameter (class radius [0 - 1 [m) and could not be identified on the 1 m precision DEM. This led to the number of trees being sharply under estimated for both stands (- 43.6 % for open stand and -70 % for the closed stand).

5. DISCUSSION

The terrain/non-terrain classification method gave very encouraging results for all the studied stands. Results concerning tree segmentation were much more "stand-dependant". The best results were obtained for the poplar plantation with high and regularly spaced trees (90 % of well identified trees). For natural pine stands the segmentation gave poor results. This was not surprising because of the complex shapes of the crowns and the irregular spatial distribution of trees. For these stands achieving an individual tree segmentation with the available data is unlikely. However interesting information concerning tree density, spatial organisation could be derived from the automatic tree crown delineation. The spatial resolution of the used DEM (1 m) allowed us to identify trees with a radius equal to that resolution. Better results are expected to be an outcome of DEM improvement. Some promising tests to obtain a 0.5m DEM from the same LiDAR data have already been performed. More information could also be derived from the complementarity of the DEM and HRI.

Future studies could be undertaken to improve the Water-

Stand	Average distance between trees (or holes) in m	Size of optimal square in m	% of correctly classified pixels	square closest to average distance	% of correctly classified pixels
Olive trees	7.8	11	91.8	8	90.6
Poplar trees	9.5 (holes)	25	98.7	10	86
Dense pine	13.3 (holes)	20	87.9	10	85.7
Sparse pine	18.2, 15.2(holes)	10	84	20	83.8
Young pine	10.2 (holes)	30	88.2	10	68.8

Table 6: Accuracy of classification

	Olive trees		Poplars	
	Nb	%of total number of trees of the stand	Nb	%of total number of trees of the stand
Trees correctly segmented	20	52.6	128	80.5
Trees correctly segmented with a problem of area	4	10.5	15	9.4
Trees over-segmented	5	13.2	2	1.3
Trees under-segmented	4	10.5	13	8.2
Trees under- and over-segmented	5	13.2	1	0.6
Trees omitted	0	0	0	0
Extra segments	0	0	18	11.3
Total number of trees in the stand	38		159	
Correct (segmentation+area)		63.2		89.9

Table 7: Comparison between automated recognition and ground reference

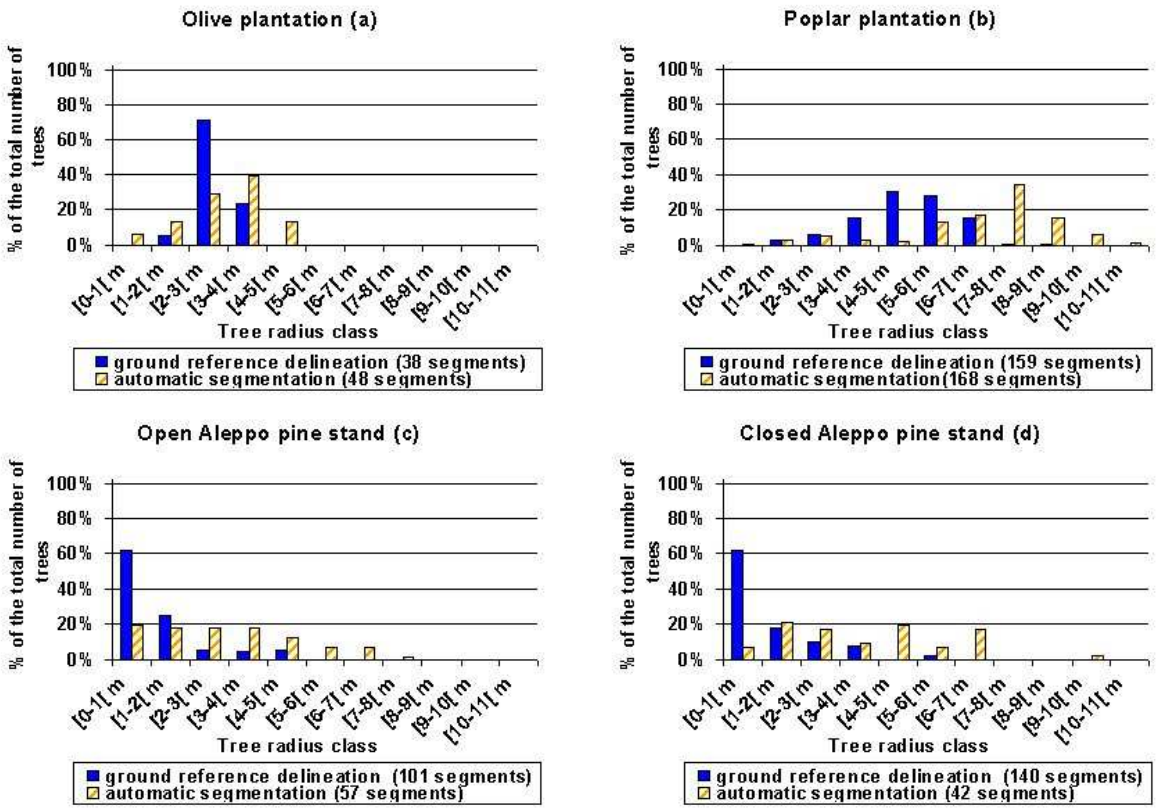

Figure 8: Figures (a) to (d) show the numbers of trees per radius classes calculated for the ground reference data and for the results of automatic delineation

shed algorithm using level sets. It would be interesting to study automatic identification of optimal square size for mixture modeling thresholding. Higher level knowledge could lead to better results by identifying tree types. Extra information can easily be extracted from the regions (tree crown diameter, height, ...) and could be used by an identification algorithm (ex : neural network) to create maps of regions automatically.

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