Applying Image Analysis and Probabilistic Techniques for Counting Olive Trees in High-resolution Satellite Images

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Abstract. This paper proposes a method, that integrates image analysis and probabilistic techniques, for counting olive trees in high-resolution satellite images. Counting trees becomes significant for surveying and inventorying forests, and in certain cases relevant for assessing estimates of the production of plantations, as it is the case of the olive trees fields. The method presented in this paper exploits the particular characteristics of parcels, i.e. a certain reticular layout and a similar appearance of trees, to yield a probabilistic measure that captures the confident of each spot in the image to be an olive tree. Some promising experimental results have been obtained in satellite images taken from QuickBird.

1 Introduction

Last years have witnessed a remarkable improvement of satellites used in remote sensing. Nowadays, commercial satellites like Quickbird, Orbview, or Ikonos provide high-resolution images that open up a promising and challenging field for the automatic detection of terrain features for a variety of purposes. Some examples of this can be found in the literature for detecting and locating human constructions, such as roads, buildings, sport fields, etc. (see [6] for a survey), and geographical features, like coastlines [7], lakes [3], mountains [11], etc.

In general, the aim of remote sensing applications is to facilitate (and insofar as it is possible, automate) monitoring tasks on large areas of terrain, for instance surveying and inventorying forests, which are normally tediously and costly performed by human operators.

In this paper we propose an image processing-based approach for counting trees, in particular olive trees, within a plantation. Counting trees bears a significant relevance for two reasons. First, it provides an inventory of the trees in the plantation that may help the farmer to a better planning of the irrigation or fertilization processes. On the other hand, information about the number of trees of a plantation becomes essential for assessing an estimate of the production, as well as for calculating the value of the field. In fact, the number of trees within parcels has been considered by the Spanish Government, following the European normative (UE law 154/75, 1975), to grant olive-trees farmers.

Typically, the process of counting trees is carried out manually by an operator who has to move around the whole plantation. Sometimes, this tedious chore is simplified by manually counting the number of trees within a relative small area (a sample region), assessing the global amount in the plantation according to its extension, the number of sampled trees, and the tree density measured in the sample region. In both cases, this process is highly prone to errors. Moreover, the active participation of operators, who may falsify the results, cause suspicions in grants.

This paper proposes the integration of different image analysis and probabilistic techniques into a system for counting olive trees in high-resolution satellite images. In such images, olive trees typically appear as dark spots of different sizes and shapes, that may largely vary from one parcel to another. This makes counting processes based on image analysis complex and dependent on several parameters for each parcel. However, in general, olive trees within a particular parcel¹ meet some common characteristics that must be considered in the image analysis process to gain in robustness and reliability: they have almost the same size (but not the same shape) and usually follow a particular reticle (reticular layout).

The procedure proposed in this paper takes advantage of these characteristics. Briefly, it first considers a representative portion of the image, given by an operator, where dark spots that fulfill a particular reticular layout are localized by means of a voting scheme. From this procedure we also obtain an estimate of how well each spot fits into that particular reticle: the higher this value, the higher the probability of a spot to be an olive tree of the parcel represented by the selected reticle. Secondly, and exploiting the similarity of trees within a given parcel (trees are usually planted at the same time, receiving the same irrigation and fertilization treatment), a prototype of the typical tree is obtained by processing the olive candidates entailed within the representative area given by the operator. The resultant prototype is used to asses the similarity of each candidate (in size and shade), as a probabilistic value, with respect to the prototype by means of Bayesian techniques [4]. The final probability of each candidate to be an olive tree will be the joint probability of both, that the spot belongs to the reticle and that it exhibits the same characteristics that the prototype. Although our work focuses on olive trees, it can be also applied to any type of plantation that follows a reticular arrangement.

In the literature only a few works have addressed the problem of counting trees through satellite images [1, 2, 8]. However all of them consider a number of parameters which have to be tuned manually for each image, even for each parcel. The main advantage of the method we propose here is that it is highly automated and the participation of human operators is limited to select the input parcel within the image to be processed and to validate the obtained results.

The structure of this paper is as follows. Section 2 gives a general description of the system. Section 3 delves into the automatic detection of tree candidates and the computation of their probabilities of being olive trees according to the

¹ A parcel is understood here as an olive field where trees were planted at the same time and with the same farming techniques, although it may not coincide with the administrative division.

reticular arrangement of the parcel. Section 4 is devoted to the computation of the prototype within a parcel and the similarity computation of candidates with respect to it. Some experimental results are shown in section 5, and finally conclusions and future work are outlined.

2 Method Description

Following [9], the diameter of olive tree crowns varies between 3 and 8 m., they exhibit a regular circular/elipsoidal shape, and usually follow a reticular layout with a separation between tress in the range 6 to 10 m. Figure 1 shows a typical satellite image of an olive field.

Therefore, given that trees normally present a similar pattern, i.e. a dark and almost circular spot upon a lighter background, a possible solution for counting trees is to perform pattern matching by correlating one of such a pattern through the image (as in [12]). However, this solution does not always work well since it is not clear that a fix pattern may capture the shape variability of olive tree crowns (even in a single parcel) as shown further on.



Fig. 1. A high-resolution olive tree field taken by the QuickBird satellite. Olive trees appear as small dark spots regularly arranged in a reticle. Though it may seem that they all exhibit a circular shape, there is a large variability due to the irregular growth of their branches.

An approximation to detect trees considering this shape variability is to locate closed contours in the image through typical computer vision techniques, i.e. *Canny edge detector*. Although this solution has been adopted in some works [2], it does not guarantee that other objects within the parcel, like rocks, machinery, buildings, etc., could also be detected as trees.

Assuming that olive trees are planted following a reticular structure within the same plantation (which hold for the 85% of the Spanish olive fields), the method presented in this paper overcomes the commented limitations by a twostages procedure (see figure 2 for a scheme of the method). In short, we firstly compute the main direction of the reticle of the parcel by processing the layout followed by the trees contained within a representative portion of the image selected by an operator (around 35 trees in our experiments). This direction is computed by means of a voting scheme which also permits us to assess a probabilistic measure about the probability of a dark spot to be an olive tree or not by only attending to its relative location within the computed reticular layout.

In a second stage, the set of trees within the selected area are also used to generate a statistical pattern that characterizes the size, shape, and also shade² of the olive trees within the parcel. This pattern, also called *prototype*, is used to compute the probability density function characterizing the appearance of the tree crowns of that reticle. By combining both estimates for each crown, c_i , named as $P(c_i \text{ is aligned})$ and $p(c_i \text{ resembles the prototype})$, the proposed method aims to detect trees with a certain similarity to the prototype and lying in a certain layout within the image, as:

 $p(c_i \text{ is an olive tree}) = p(c_i \text{ is aligned}, c_i \text{ resembles the prototype}) = P(c_i \text{ is aligned}) * p(c_i \text{ resembles the prototype})$ (1)

In (1) we are assuming the independence of the two sources of information. Next sections describe in more detail each phase of our method.

3 Locating Olive Tree Candidates within the Reticle

In this stage we rely on image processing techniques to locate the "center" of olive tree candidates (dark spots in the image). After that, the main direction of the reticle of the parcel is calculated based on a voting scheme applied on the trees within the representative window selected by an operator.

3.1 Localizing centroids of candidates

To locate olive tree candidates, we firstly compute the closed contours of the image through the *Canny operator*. Experimentally we have checked that this operator works well in our images with $\sigma = 0.45$.

Figure 3 (left) shows the result of this operation on a typical olive field. Since at this stage we are not concerned on the shape of the trees, mainly because of their variability, but on their localization, we compute the centroid of each found contour through the *chamfer* distance transform [5]. The result is a set of points (figure 3 (right)) that localize the centers of the tree crowns (typically near their trunks)

 $^{^{2}}$ We only use gray-scale images which provide good results. The use of color images has not improved our results since trees, especially olive trees, exhibit almost the same color in satellite images. Other source of information, like infrared images (not considered in our work), could be employed to assess the vegetation rate [10].

draft version



Fig. 2. The proposed method. Initially, an operator selects a representative window of the image, from which the main orientation of the reticular layout and a prototype of the trees is computed. This information is used to probabilistically characterize a tree in the reticle and from that, to look for the rest of candidates.



Fig. 3. Locating olive tree candidates. a) Result of the Canny operator. b) Centroids computation for each contour.

3.2 Detecting Candidates within a given Reticle

Results from the previous step is largely prone to provide false positives. On one hand, elements in the field, like rocks or machinery, and shadows on the terrain may give raise to contours similar in size to that of the olive trees. On the other hand, crown shapes may induce the detection of more than one contour, and thus, more than one centroid. For these reasons, we exploit the common characteristic presented in olive tree plantations of arranging the field in a reticular structure (see fig. 4).



Fig. 4. The reticular arrangement of trees.

In this reticular arrangement, each tree forms a certain angle, ϕ , with its neighbors, which repeats at increments of 45°. In our approach we rely on a voting scheme in which the centroids of the trees selected by the operator vote for a certain angle ϕ^* if it forms an angle $\phi = n \cdot 45 + \phi^*$ with a close neighbor. Obviously, centroids are not perfectly aligned and, thus, we account for a certain tolerance in the computation of that angle. Concretely, we divide the angle range $[0, 45^\circ]$ into 18 buckets of 5° which becomes the permitted angular interval to decide that two trees are aligned. Consecutive buckets overlap 2.5°, i.e. [0, 5], (2.5, 7.5], (5, 10], (7.5, 12.5]..., to permit angles that fall within the limit



of a bucket to also vote for the adjacent one. The bucket which receives the maximum votes, B_w , characterizes the orientation of the reticle (see fig. 5).

Fig. 5. Voting process. Angles between the centroids of the representative window are computed and grouped in buckets. The most voted one (in this example B_1) represents the main orientation of the reticle. Then, the process is repeated for the rest of centroids, assesing their votes for the winner bucket with respect to their votes to others.

Once the reticle orientation is computed, a probabilistic measure for all the trees within the parcel is calculated taking into account how well their centroids fit on it. To do this, we repeat the voting process, calculating for each candidate centroid the proportion of its votes for B_w with respect to sum of all its votes. This ratio is taken as an estimate of the probability of the membership of each tree candidate c_i to a given reticle, that is:

$$P(c_j \text{ is aligned with the reticle}) = \frac{votes_{B_w}^j}{\substack{\# \text{ of } buckets \\ \sum_{i=1}^{j} votes_{B_i}^j}}$$
(2)

4 Classification of Candidates as Olive Trees

The aim of this phase is to discard candidates that, even belonging to the reticular arrangement of the field, do not fit onto the olive appearance of the parcel. Olives trees within a parcel normally share some common characteristics, like their color or size, but not the same shape, which may exhibit a great variability. To capture this shape variability we rely on the computation of a tree prototype based on statistical measures (mean and variance). The distance from a candidate tree to this prototype will give us the likelihood of that candidate to be an olive tree based on its appearance.

4.1 Computation of the Olive Tree Prototype

The olive tree prototype for a given parcel is calculated according to the characteristics of the representative olive trees selected by the operator. To compute that prototype, an image window centered at each centroid is considered. The size (k) of this windows should be large enough to contain the tree crown and also part of the terrain (whose color is almost constant within parcels). The size of this window (typically around 15×15 pixels in our experiments) is automatically calculated according to the average area of the representative contours and their relative distance within the reticle. The prototype is then characterized by a k^2 -dimensional mean vector (μ) and a $k^2 \times k^2$ -dimensional covariance matrix (Σ) of the pixel gray-levels in the windows, computed as follows.

Let the m representative candidates, be:

$$c_{1}^{r} = [I(a_{1}, b_{1} : b_{1} + k - 1) \ I(a_{1} + 1, b_{1} : b_{1} + k - 1) \ \dots \ I(a_{1} + k - 1, b_{1} : b_{1} + k - 1)]^{T}$$

$$c_{2}^{r} = [I(a_{2}, b_{2} : b_{2} + k - 1) \ I(a_{2} + 1, b_{2} : b_{2} + k - 1) \ \dots \ I(a_{2} + k - 1, b_{2} : b_{2} + k - 1)]^{T}$$

$$\cdots$$

$$c_{m}^{r} = [I(a_{m}, b_{m} : b_{m} + k - 1) \ I(a_{m} + 1, b_{m} : b_{m} + k - 1) \ \dots \ I(a_{m} + k - 1, b_{m} : b_{m} + k - 1)]^{T}$$
(3)

where a_i, b_i are the upper-left corners of the windows centered at the centroids of the candidates c_i^r . The μ vector and the covariance matrix are calculated as:

$$\mu = \frac{1}{m} \sum_{i=1}^{m} c_i^r \qquad \qquad \Sigma = \frac{1}{m} \sum_{i=1}^{m} (c_i^r - \mu) * (c_i^r - \mu)^T \qquad (4)$$

Note that μ captures the mean gray-level of pixels of trees, and thus, their mean shape, but does not consider the high variability caused by their branches, and thus techniques based on template matching [12] are not suitable here. This variability is captured by the covariance matrix Σ : lower variance indicates low variability in the gray-level of the corresponding pixel. In figure 6 these measures are illustrated by depicting μ and Σ as images for a better understanding. For that, the k^2 elements of μ and of the diagonal of Σ have been orderly placed forming two $k \times k$ images. In those images, note that the mean shape of the representative candidates is almost circular, and that the representation of the diagonal Σ contains dark pixels (low variance) in the center part that account for the center of tree crowns but high values (large variability) around it, capturing the variability of tree shapes. The portion that contains part of the ground also



Fig. 6. Prototype computation. Note the differences in the shape of the candidates. This high variability is captured by the mean vector μ and the covariance matrix Σ . M(i,j) shows an image that represent the values of μ while E(i,j) shows the diagonal of Σ , for which dark values indicates low variability (the center of the tree crowns) and lighter values, high variability (the shape of the branches).

presents a low variability because of the similarity of the terrain color within parcels.

4.2 Measuring Similarity to the Prototype

Using the prototype characterized by μ and Σ we estimate the similarity of a candidate, c_i , given by a $k \times k$ window centered at a centroid contour, through the gaussian density probability function given by:

$$p(c_i) = \frac{1}{(2\pi)^{k^2} |\Sigma|^{1/2}} e^{-\frac{1}{2}(c_i - \mu)^T \Sigma^{-1}(c_i - \mu)}$$
(5)

This likelihood measure can be considered as an estimate of $p(c_i \text{ resembles})$ the prototype): the higher the similarity of the candidate c_i to the prototype characterized by μ and Σ , the higher the value of $p(c_i)$.

4.3 Classifying the Candidates

Finally, in order to decide if a candidate, c_i , is an olive tree, we set a minimum threshold for its joint probability. This threshold value is taken as the lowest value of p(x) yielded by the representative trees. That is, c_i is considered as an olive tree iff:

$$p(c_i \text{ is olive tree}) = (P(c_i \text{ is aligned}) * p(c_i)) \ge \tau, \text{ where}$$

$$\tau = min(p(x), x \in c_1^r, \dots, c_m^r)$$
(6)

4.4 Experimental Result

Our method has been tested with panchromatic QuickBird images (0.6 meter/pixel of spatial resolution) of a region in the South of Spain. We have considered images of parcels containing, in average, around 2000 trees of different varieties, sizes, and reticle orientations. It has been implemented in C++ using the image processing library "OpenCV" [13]. Our implementation has been integrated as an extension of the commercial package ESRI©ArcView, a GIS software commonly used by the remote sensing community. Figure 7 shows two snapshots of the application.



Fig. 7. Two snapshots of ESRI©ArcView running the olive tree counting software. In the figures, the process has been limited to a particular administrative area selected by the user.

In order to test the suitability of the proposed method we have compared its results to the number of trees visually counted by an operator from color aerial orthophotos. In this comparison we have differentiated false- positives (FP) and negatives (FN). A candidate is set to be FP if it is erroneously detected as an olive tree and FN if it is erroneously detected as a non-olive tree.

For three of our test images we have obtained the results shown in table 1.

Number of olive trees (Ground Truth)	Detected Trees	FP	$_{\rm FN}$
2324	2293 (98.66%)	10 (0.43%)	21 (0.9%)
2109	2072 (98.24%)	15~(0.71%)	22~(1.04%)
2549	2530 (99.25%	11 (0.43%)	8 (0.31%)
Table 1 Some regults of our method			

 Table 1. Some results of our method.

Although the resultant figures of our method are promising, it still generates a number of false positives/negatives. They are mainly produced because our main

assumption about the characteristics of parcels (reticular layout and similarity of tree sizes) is not always met. Concretely, FN are due to the presence of candidates misaligned with respect to the reticle, since sometimes farmers plant trees out of the reticle for a best use of the space at the limits of their parcels (as shown in figure 8a-left). On the contrary, in some cases a tree within the reticle needs to be cut and replanted, being then smaller than the rest (see figure 8a-right). In both cases, the joint probability falls down under the considered threshold because the candidate deviates significatively from the representative ones. Regarding FP, it occasionally appears candidates that even fulfilling the imposed requirements to be an olive tree they actually are not. This is the case illustrated in figure 8b, where there is a small orchard that entails trees with the same characteristics that the prototype and reticular layout of the parcel.



Fig. 8. Examples of misleading results. a) Two cases of false negatives yielded by the method: left) FN due to an olive tree misaligned with the reticle; right) FN caused by an olive tree largely different with respect to the rest of the parcel. b) Example of a false positive. Trees (or in general objects) in the image fulfilling the requirements of size and reticular arrangement of a parcel will be detected, although, like in this case, they can be trees in a near orchard.

5 Conclusions and Future Works

This paper has presented a probabilistic image-based method for counting olive trees in high-resolution satellite images. The proposed procedure takes into account the inherent characteristics of olive tree fields: the reticular layout of trees and their similar size (but not shape).

Our method has been implemented and tested in several images of the South of Spain taken from the QuickBird satellite with promising results.

In the near future we plan to test our method with color and aerial images in order to improve the results.

Acknowledgments

©DigitalGlobe QuickBird imagery used in this study is distributed by Eurimage, SpA. (www.eurimage.com) and provided by Decasat Ingenieria S.L. (www.decasat.com). This work was partly supported by the Spanish Government under research contract DPI2005-01391.

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