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TOWARDS AUTOMATIC OLIVE TREE EXTRACTION FROM SATELLITE IMAGERY

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ABSTRACT:

In this paper an approach towards the automatic olive tree extraction from satellite imagery is presented. Counting olive trees in specific agriculture areas is crucial for the European Union olive production subsidies. Still counting and verification of each producer's subsidy are based on standard photointerpretation methods or semi automatic techniques. In this paper an image processing scheme towards automatic olive tree extraction was developed and applied to satellite imagery. The processing scheme is composed of two steps. In the first step, enhancement and smoothing was performed using nonlinear diffusion. In the second step, olive tree extraction was accomplished after extracting the local spatial maxima of the Laplacian. Results appear promising and counting errors mostly occur in cases where olive trees can not even be detected well by standard photointerpretation methods.

1. INTRODUCTION

The European Economic Community since 1975 (EEC, 1975) has placed regulations concerning the management of the olive oil market sector, concentrated in five member states of the European Union (EU), currently oblige an onerous survey of producers' trees in order to justify subsidies. The main purpose of the survey was to establish a register, thus providing a basis for the payment and checking of aid to farmers (Kay et al., 1997).

In September 1997 the EC (DGVI, Agriculture) launched the "OLISTAT" project with the goal to estimate the number of olive trees in France, Italy, Spain, Portugal and Greece.

The regulatory context, parcel-level requirement for data and complex agronomic characteristics (irregular, mixed, etc.) of olive tree stands (plantations) demands an object-identification approach.

The counting of trees is a classic forestry application in remote sensing data. Crown counting can be difficult and inaccurate. Much depends on the quality of the image data, the physiognomy of the stand, and the skill and experience of the photointerpreter. Howard (1991) cites a minimum spacing of $\pm 4m$ between trees for large scale aerial photography, and that most accurate counts can be obtained in boreal forests, open grown woodlands and recently thinned plantations.

In response to a direct requirement of the EC and Member States (EEC, 1997) to manage some 500 million olive trees in the Mediterranean countries, the Agricultural Information Systems Unit (of the Space Applications Institute, JRC) developed an algorithm and software application for the computer-assisted counting of trees (Kay et al., 2000).

The algorithm uses serially a binary threshold, a region growing technique and a testing of shape and size criteria technique. It operates on four main parameters and as one has to input both min and max values (threshold range and shape parameters), at the end there are seven parameters that control the output of the algorithm.

A fast and efficient algorithm, with fixed parameters, is proposed in this paper towards automatic olive tree extraction. The comparative advantage of the algorithm is that it pays

attention in the pre-processing step during which image selective smoothing is accomplished.

The pre-processing step is crucial since automatic feature extraction requires a processing system to encapsulate the content of the image. This is a non-trivial task, because of the complexity of the information stored in images (Granlund, 1999).

Feature extraction results are directly related to the performance of the initial enhancement and smoothing stage (Argialas, 1990; Adelman, 1999; Gulch, 2000; Mikhail, 2000; Karantzas et al., 2002a; Karantzas and Argialas, 2002b) and this is why this proposed algorithm seems to have advantages compared to earlier efforts in olive tree extraction, especially in the typical problems of shadowing and irregular stands.

2. BACKGROUND

2.1 Image Selective Smoothing

Diffusion algorithms remove noise from an image by modifying the image via a partial differential equation (PDE). As shown by Koenderink (1984) convolution of the original image $I(x, y)$ with the Gaussian filter is the general solution of the partial differential equation (1). Perona and Malik (Perona, 1990) replaced the classical isotropic diffusion equation with (2)

$$\partial I(x, y, t) / \partial t = \text{div}(\nabla I) \quad (1)$$

$$\partial I(x, y, t) / \partial t = \text{div}[g(\|\nabla I\|)\nabla I] \quad (2)$$

where

div is the divergence operator,
 $\|\nabla I\|$ is the gradient magnitude and
 g is an "edge-stopping" function.

Research in this area has been oriented toward understanding the mathematical properties of anisotropic diffusion and related variational formulations, developing related well-posed and stable equations and extending and modifying anisotropic diffusion for fast and accurate implementations (Alvarez, 1992; Catte, 1992; Rudin, 1992; Alvarez, 1993; You 1996). A comprehensive investigation of using several different types of partial differential equations (PDEs) has been made by Weickert (1998) for a number of computer vision applications. In this paper the nonlinear parabolic equation (3) (Alvarez, 1992) is used for an image selective enhancement and smoothing, which can smooth regions and at the same time prevents edge blurring.

$$\mathcal{H}I(x, y, t) / \mathcal{H}t = g(|G * \nabla I|) |\nabla I| \operatorname{div} \left(\frac{\nabla I}{|\nabla I|} \right) \quad (3)$$

The term $|\nabla I| \operatorname{div} \left(\frac{\nabla I}{|\nabla I|} \right)$ diffuses the image $I(x, y)$ in the direction orthogonal to its gradient $|\nabla I|$ and does not diffuse it at all in the direction of $|\nabla I|$. The term $g(|G * \nabla I|)$ is used for the enhancement of the edges.

A robust anisotropic diffusion filtering proposed by Black and Sapiro (Black, 1998) has also been tested. Roughly speaking it's a statistical interpretation of anisotropic diffusion, specifically, from the point of view of robust statistics, which uses *Tukey's* biweight robust error norm for "edge-stopping" function. It has been also used in combination with alternating sequential filtering (Karantzalos, 2003) for satellite image enhancement and smoothing with promising results.

It was not used in this case due to its (slightly more) time consuming implementation and because in general it did not significantly improved the results.

2.2 Blob Detection

In a greyscale image $I(x, y)$ the first order derivative ∇I (Gradient) is defined in equation (4) and the second order in equation (5) with the help of the Hessian matrix H_I . The Laplacian is an irreducible differential invariant (Koenderink, 1984) and blobs can be defined by local spatial extrema of the Laplacian (6).

$$\nabla I = (I_x, I_y) \quad (4)$$

$$H_I = \begin{pmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{pmatrix} \quad (5)$$

$$\nabla^2 I = I_{xx} + I_{yy} \quad (6)$$

When for the second order derivative in a specific point in the image: $I_x^2 + I_y^2 = 0$ and the $\det(H_I) > 0$, then the point is called an Elliptic Point due to image surface appearance in that area, depending on the sign of the Laplacian, see Figure 1. Extracting blobs in an image is looking for local spatial extrema of the Laplacian $\nabla^2 I$, or equivalently detect the zerocrossings of its gradient, hence

$$\nabla(\nabla^2 I) = 0 \quad (7)$$

The sign of $\nabla^2 I$ dictates whether it is a bright blob (intensity maxima, $\nabla^2 I < 0$) or a dark blob (intensity minima, $\nabla^2 I > 0$).

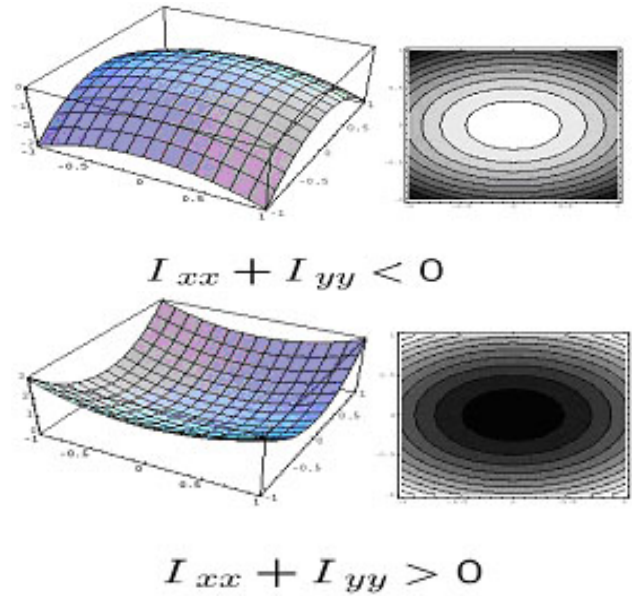


Figure 1. The appearance of Elliptic Points depends on its sign of the Laplacian.

3. METHODOLOGY

The developed in this paper processing scheme constitutes two steps. In the first step enhancement and smoothing is performed using nonlinear diffusion. In the second step olive tree extraction is accomplished after locating the local spatial maxima of the Laplacian.

The approach is essentially morphometric, and spatial resolution is therefore of highest importance in the image recognition of the trees. Productive olive trees typically have crowns of 3m to 12m in diameter, with a spacing of 6m to 10m in regular stands (Kay et al., 2000). Suitable data, therefore, for this operation are scanned panchromatic aerial photography, with a pixel size of 0.8m-4m, typically derived from high resolution 1:40,000 scale flights and satellite imagery from IKONOS and QUICKBIRD.

3.1 Olive Tree Extraction

Combining the nonlinear diffusion and the blob detection technique olive trees can be extracted from satellite imagery. First, image selective smoothing by nonlinear diffusion is applied leading to sharper discontinuities among different features. Equation (8) was chosen for the "diffusion-stopping" function because it privileges high contrast edges against low contrast edges, while function (9) privileges wide region over small region and olive trees generally possess smaller regions compared to other field segments in their neighbourhood.

$$g(\|G * \nabla I\|) = e^{-\|G * \nabla I\|/K} \quad (8)$$

$$g(\|G * \nabla I\|) = 1/1 + (\|G * \nabla I\|/K)^2 \quad (9)$$

Second, the blob detection technique is applied and the local spatial maxima of the Laplacian $\nabla^2 I$ are extracted. Olive blobs appearing in the binary image are labelled and their number is counted.

The algorithm is quit fast even in a simple Matlab implementation and always according to the number of iterations during anisotropic diffusion.

4. RESULTS AND DISCUSSION

The algorithm was tested in IKONOS and QUICKBIRD imagery. In the image selective smoothing step a number of 40 to 50 iterations gave fast and desired results for a successful local spatial maxima extraction.

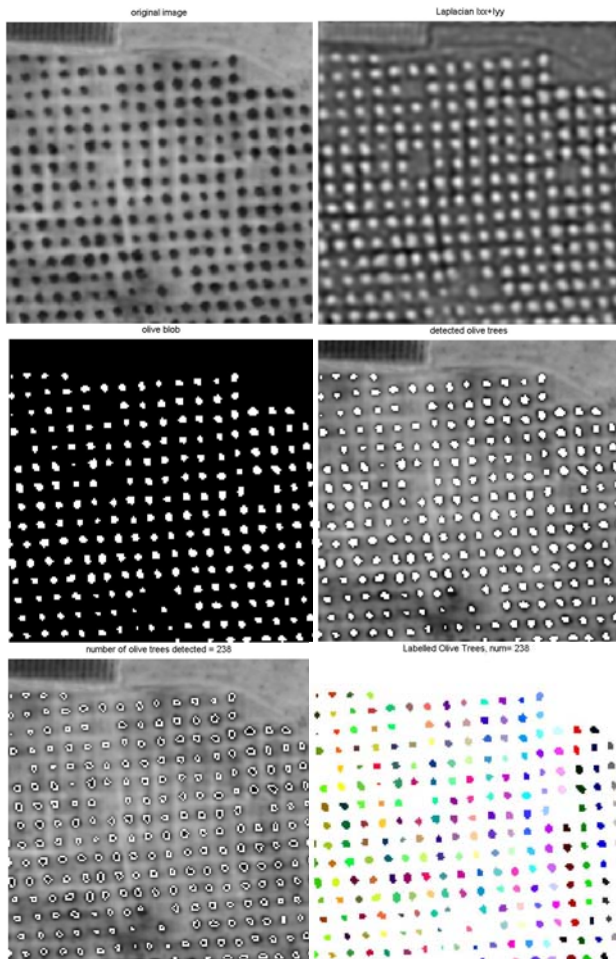


Figure 2. Olive tree extraction and numbering in a QUICKBIRD 1 meter ground resolution image.

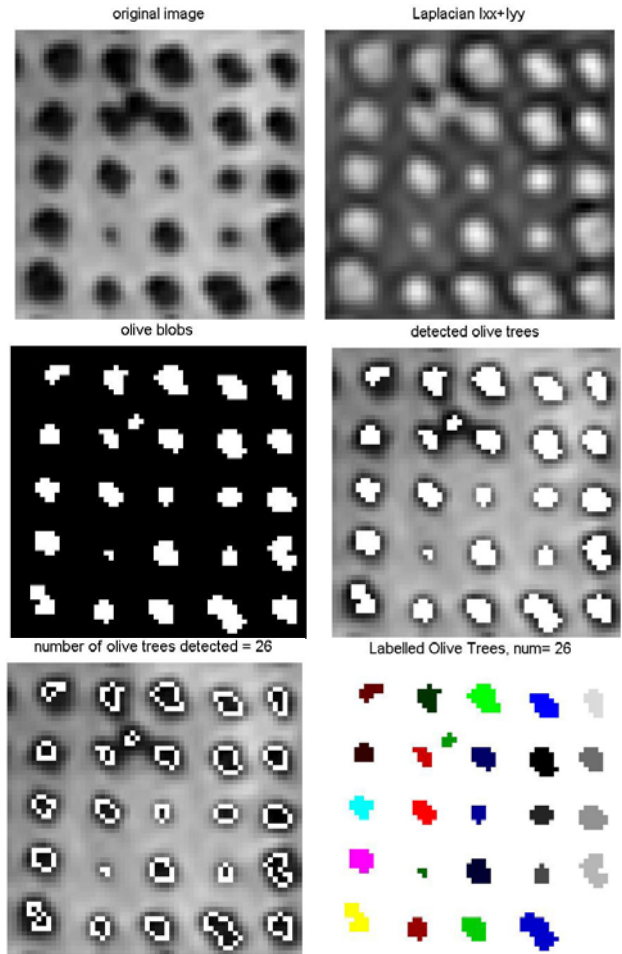


Figure 3. Olive tree extraction and numbering in a QUICKBIRD 1 meter ground resolution image.

Although coalesced crowns, heavy shadowing or the non-resolution of young plants will always introduce errors into a remote sensing-derived count (Howard, 1991), the algorithm operates successfully almost in all cases.

In Figure 2 olive trees are extracted and numbered from a 1 meter ground resolution QUICKBIRD image, taken during spring. The red band was chosen to apply the algorithm to, due to its better contrast. In this case of a relatively “easy” image the algorithm was totally correct.

In Figure 3 it is shown that the algorithm overcomes problems due to the variation of crown shapes, sizes and densities. A bunch of three coalesced crowns were numbered correctly and all olive trees (even the non-resolution of young plants) were correctly identified.

A summer IKONOS 4 meter resolution (red band) image is shown in Figure 4 together with the results of the algorithm. It is not an “easy” image for olive tree detection since it presents a couple of different parcels, coalesced crowns, heavy shadowing and irregular stands. The algorithm works well and counts correctly the number of olive trees.

In Figure 5 it is shown that the algorithm operates in SPOT HRV images (10 meter resolution), too. Counting errors mostly occur in cases where olive trees can not even be detected correctly by standard photointerpretation methods.

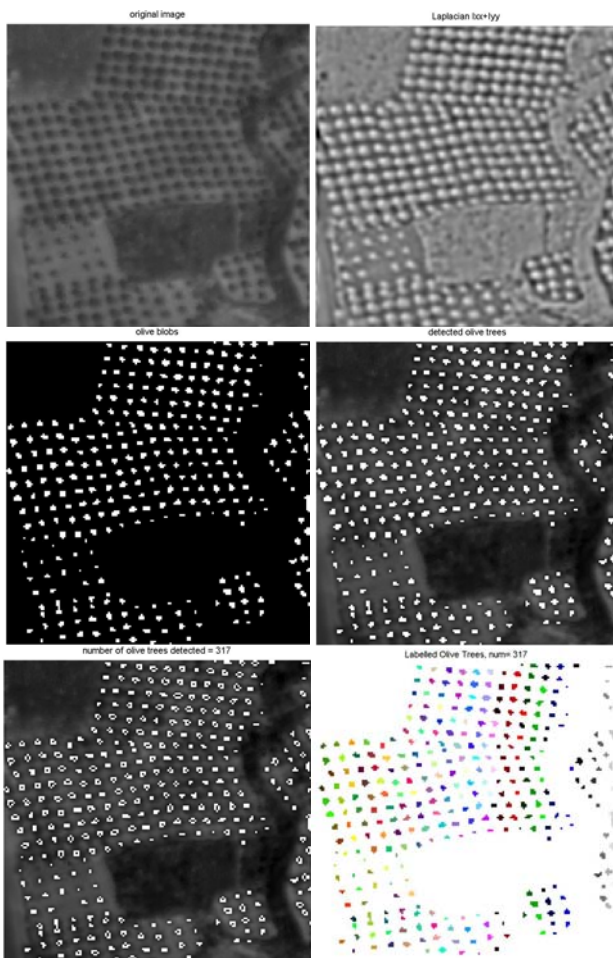


Figure 4. Olive tree extraction and numbering in an IKONOS 4 meter ground resolution image.

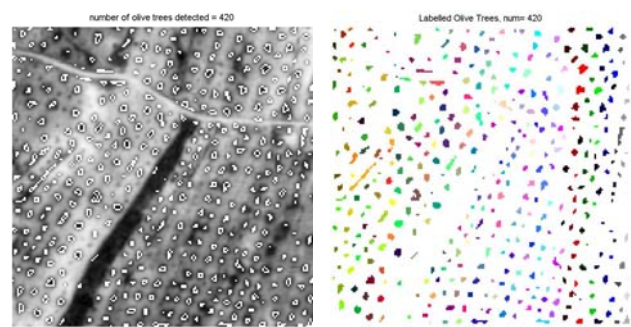
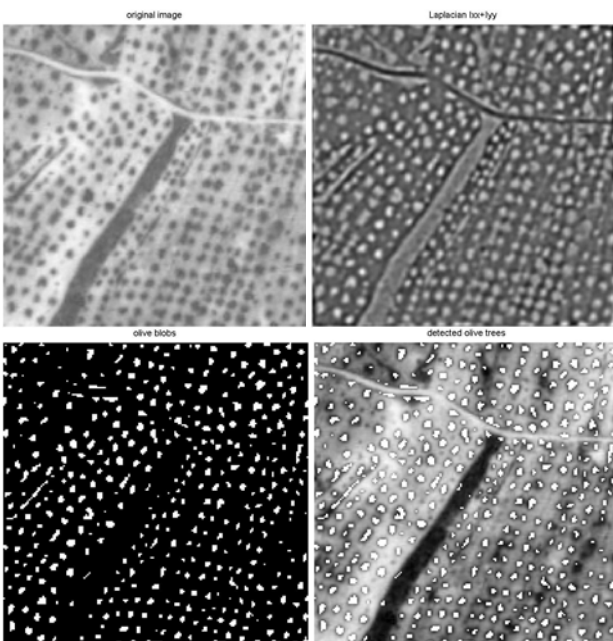


Figure 5. Olive tree Extraction in a SPOT panchromatic 10 meter ground resolution image.

5. CONCLUSIONS AND PROSPECT

In this paper an approach towards automatic olive tree extraction from satellite imagery was presented that seems to outperform earlier algorithms. The output is a list of identified and labeled olive trees and it can be extended to include geographic coordinates. Combining the algorithm with a vector processing toolbox or software which handles GIS data of olive tree parcel properties, it can efficiently be used for providing a basis for the subsidies.

In addition, it can be applied to forest inventory approaches for the estimation of tree numbers or their derivative products, such as timber volume.

As a prospect automatic scale selection during blob detection can also be used from scale space theory to deal with the variation of crown sizes and shapes.

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