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Improving edge detection and watershed segmentation with anisotropic diffusion and morphological levellings

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Edge preserving smoothing and image simplification is of fundamental importance in a variety of remote sensing applications during feature extraction and object detection procedures. The construction of a pre-processing filtering tool for edge detection and segmentation tasks is still an open matter. Towards this end, this paper brings together two advanced nonlinear scale space representations, anisotropic diffusion filtering and morphological levellings, forming a processing scheme by their combination. The proposed scheme was applied to edge detection and watershed segmentation tasks. The experimental results showed that the developed scheme generated an effective pre-processing tool for automatic olive tree detection and solving watershed over-segmentation problems.

1. Introduction

Aerial and satellite sensor images provide a wealth of information. Remote sensing digital processing systems provide opportunities for mapping and monitoring the state of the global environment, with increasing levels of automation (Jensen 2000, Rogan and Chen 2004). Automatic feature extraction procedures require a processing scheme able to encapsulate the content of remote sensing images by efficiently detecting desired object boundaries in the step of edge detection or segmentation. During these steps the degree of how well desired object boundaries (primitives usually described in binary images) have been detected, plays a key role for the overall efficiency of the automatic feature extraction procedure (Argialas and Harlow 1990, Paragios *et al*. 2005).

It should be pointed out that the landscape structure is complex, being a combination of many different intensities, representing natural features such as vegetation, geomorphological and hydrological features, human-made objects (buildings and roads) and artefacts caused by variation in illumination of the terrain (shadows). Roads, infrastructure, vegetation, landforms and other land features appear in different sizes and geographical scales in images (e.g. country road versus interstate, tree stands versus forest, maisonette versus polygon building and rill versus river). In only a few 'lucky' circumstances, the objects of interest that have to be detected, measured, segmented, or recognized in an image belong to a certain scale, and all remaining objects, to be discarded, to another (Meyer and

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Maragos 2000). In most cases, however, such a scale threshold is not possible since the desired information is present at several scales. For such situations, multiscale filtering approaches have been developed, where a series of coarser and coarser representations of the same image are computed (Hay *et al.* 2003, Paragios *et al.* 2005) and are used for the recognition of objects.

Anisotropic diffusion filtering (ADF) and morphological levellings (ML) are nonlinear multiscale operators with many interesting properties (Weickert 1998, Soille and Pesaresi 2002, Meyer 2004). They can highlight the distinction between the features in an image so that on the one hand visual quality is improved and on the other hand they facilitate edge detection and segmentation techniques. Especially with the use of ML filtering, details vanish from one scale to the next but the contours of the remaining objects are preserved sharp and perfectly localized (Meyer and Maragos 2000). Hence, objects are enhanced so that the edge detection or segmentation operators can detect the location of the object boundaries.

This paper brings together the two advanced nonlinear scale space representations of ADF and ML for automatic feature extraction for remote sensing applications. The motivation was to demonstrate that their sequential combination is effective and constitutes a powerful pre-processing tool for edge detection and watershed segmentation.

2. Combining anisotropic diffusion and morphological levellings

Both ADF and ML are multiscale operators with interesting and valuable properties. The goal was to obtain the major advantages of each filter, try to synthesize them and investigate the possibility for an effective filtering result for remote sensing imagery. Here follows only a brief description of both methods. For an extensive analysis of ADF and ML one can refer to Weickert (1998) and Meyer (1998), respectively.

2.1 *Anisotropic diffusion filtering*

Anisotropic diffusion was formulated by Perona and Malik (PM) (Perona and Malik 1990), who replaced the classical isotropic diffusion equation with:

$$\vartheta I(x, y, t)/\vartheta t = div[r(\|\nabla I\|)\nabla I] \tag{1}$$

where $\|\nabla I\|$ is the gradient magnitude and r is an 'edge-stopping' function. Since this elegant formulation of anisotropic diffusion, a considerable amount of research has been devoted to the theoretical and practical understanding of the mathematical properties of ADF and related variational formulations, developing related well-posed and stable equations and extending and modifying anisotropic diffusion for fast and accurate implementations (Weickert 1998). Among them one can find the geometry-driven diffusion by Alvarez, Lions and Morel (ALM) (Alvarez *et al.* 1992), and the robust anisotropic diffusion filtering proposed by Black and Sapiro (BS) (Black and Sapiro 1998). The ALM approach is based on the following PDE:

$$\vartheta I(x, y, t)/\vartheta t = r(|G_\sigma * \nabla I|)|\nabla I| div\left(\frac{\nabla I}{|\nabla I|}\right) \tag{2}$$

The term $|\nabla I| div(\nabla I/|\nabla I|)$ 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 contrast term $r(|G_\sigma * \nabla I|)$ is used for the enhancement of the edges as it controls the speed of diffusion. G_σ is a smoothing kernel (2-dimensional Gaussian function) and thus $|G_\sigma * \nabla I|$ is a local estimate of $|\nabla I|$ for noise elimination. Similarly with equation (2), r is an 'edge-stopping' smooth and non-increasing function:

$$r(0) = 1, \ r(k) \geq 0, \ \textit{and} \ \lim_{x \to \infty} r(k) = 0 \tag{3}$$

which tends to zero as k tends to infinity. This anisotropic process reduces the diffusivity at those locations that have a larger likelihood of being edges based on their larger gradients. If $|\nabla I|$ is small, then the diffusion is strong. If $|\nabla I|$ is large at a certain pixel (x, y), this pixel is considered as an edge point, and the diffusion is weak.

Roughly speaking, the BS robust anisotropic filtering approach is a statistical interpretation of anisotropic diffusion, and more specifically from the point of view of robust statistics. BS filtering uses the Tukey's biweight robust error norm as the 'edge-stopping' function and this forms a robust estimation framework, which estimates a piecewise smooth image from a 'noisy' input image. Karantzalos (2003) employed BS filtering in combination with alternating sequential filtering for satellite image enhancement and smoothing with promising results.

Among the PM, ALM and BS anisotropic filtering, the ALM filtering was selected here to accompany ML. PM filtering, which reserves the average luminance value during diffusion, was not as elegant as the other two and yielded a more abrupt diffusion. BS filtering was not selected due to its (slightly more) time consuming implementation and its rather similar behaviour with ALM for a small number of iterations.

2.2 *Morphological levellings*

The theory and implementations behind the nonlinear scale-spaces with multiscale morphological filters considers the evolution of curves and surfaces as a function of their geometry. The standard morphological openings (which are serial compositions of dilations and erosions) preserve vertical image edges well but may displace the horizontal contours; however, they do not create spurious extrema (Meyer and Maragos 2000). A more powerful class of morphological filters that can also preserve the horizontal contours is the openings and closings by reconstruction. These filters, starting from a reference signal f consisting of several parts and a marker (initial seed) g inside some of these parts, can reconstruct whole objects with exact preservation of their boundaries and edges. In this reconstruction process they simplify the original image by completely eliminating smaller objects inside which the marker cannot fit. However, one of their disadvantages is that they treat the image foreground (peaks) and background (valleys) asymmetrically (Meyer and Maragos 2000).

A recent solution to this asymmetry problem came from the development of a more general powerful class of self-dual morphological filters, the levellings, introduced by Meyer (1998), which include reconstruction openings and closings as a special case. Recently they have been proposed as an effective tool for image simplification and segmentation (Vachier 2001, Meyer 2004). Soille and Pesaresi (2002) have also described them as an advanced mathematical morphology tool for geoscience and remote sensing applications.

Considering that a light region (respectively a dark region) is marked by a regional maximum (respectively a regional minimum), one should look for connected operators that do not create any new extremum and which do not exchange a maximum of a minimum (and conversely). Being able to compare the values of 'neighbouring pixels' one can define levellings as a subclass of connected operators that preserve the grey-level order. Levellings are transformations $\Lambda(f, g)$ and in mathematical terms, based on a lattice framework, an image g is a levelling of the image f if and only if for all neighbouring points in space (all neighbour pixels $\forall(p, q)$) the following equation holds:

$$g_p > g_q \Rightarrow f_p > g_p \text{ and } g_q \geq f_q \tag{4}$$

Levellings are created when associated to an arbitrary family of marker functions. These multiscale markers can be obtained from sampling a Gaussian scale-space (Meyer and Maragos 2000). Let there be an original image $f(p, q)$ and a leveling Λ. Assuming that one can produce markers $h_i(p, q)$, $i=1, 2, 3, \ldots$, associated with an increasing scale parameter i and calculate the levelling $\Lambda(h_i, f)$ of image f based on these markers, a multiscale representation can be produced:

$$g_1 = \Lambda(h_1|f),\ g_2 = \Lambda(h_2|g_1),\ \ldots,\ g_n = \Lambda(h_n|g_{n-1}) \tag{5}$$

The above equation implies that g_j is a levelling of g_i, for $j>i$. Here the sequence of markers h_i is obtained from the original image f by a convolution with a 2-dimensional Gaussian filter. Hence the scale parameter i corresponds to the standard deviation of the Gaussian function. A Gaussian marker h is transformed until it becomes a function g which is a levelling of f.

2.3 *The developed processing scheme*

Taking into account that all anisotropic diffusion methods on the one hand do reduce edge blurring but do not eliminate it completely, since spurious extrema may still appear (Weickert 1999, Meyer and Maragos 2000) and on the other hand they do not take into account the geometry of image objects, their single use leads to a limited success. In parallel, ML do consider the evolution of image objects as a function of their geometry and do combine a perfect localization of the contours with efficient suppression of detail (Meyer 1998, Meyer and Maragos 2000).

The developed scheme used the ADF result, derived from the geometry-driven diffusion by Alvarez *et al.* (1992), as the reference image for the ML, instead of the original image. In this novel framework the ML was dominated by an already nicely enhanced and smoothed image in which edges and abrupt intensity changes have been respected, since in all cases ADF was performed with a small number of iterations (the goal was just to obtain a slightly smoothed version of the original image). With such a reference image the multiscale markers obtained from sampling its Gaussian scale-space did not start blurring the original image but they started by blurring the ADF output. This theoretically is expected to yield a more edge preserving, geometric driven, image simplification and therefore enhance, smooth and simplify the image, so that the edge detector or segmentation technique, which will follow, will be able to detect where the desired object boundaries are.

In mathematical terms the developed scheme can be described by the following equation:

$$g_i = \Lambda\left(h_i,\ \frac{\vartheta I(x, y, t)}{\vartheta t}\right) \tag{6}$$

where I is the original image, Λ is the levelling transformation, $\vartheta I(x, y, t)/\vartheta t$ is the output of the ADF (equation (2)), h_i is the multiscale Gaussian marker and g_i is the final output of the developed processing scheme. The scheme is controlled by the two scale parameters t and i, where t is the number of ADF iterations and i the scale of the ML.

3. Experimental results and discussion

The effectiveness of the developed processing scheme is demonstrated for the critical low level computer vision tasks of image smoothing and simplification. These tasks are almost always used as the vital pre-processing step towards automatic feature extraction and object detection based on edge detection or segmentation techniques.

3.1 *Edge detection*

The developed filtering scheme was used to increase the efficiency of edge detection and, in particular, was applied for automatic olive tree extraction from a high spatial resolution IKONOS PAN satellite sensor image. Karantzalos and Argialas (2004) used a single application of the nonlinear diffusion by Alvarez *et al.* (1992) (ALM) and combined it with local spatial maxima extraction of the Laplacian. In figure 1, the developed scheme is compared with: (i) morphological levelling with scale 3 (structure element size, parameter i), (ii) classic anisotropic diffusion of Perona and Malik (1990), (iii) ALM filtering and (iv) Black and Sapiro (1998) robust anisotropic diffusion (BS). In all cases, the diffusion was stopped after 60 iterations (parameter t). The developed scheme, as shown in figure 1, outperformed all the others: after a close look in figure 1 (last raw, zoom on a specific crop) one can observe that the application of the developed scheme closes curves that describe all extracted olive tree boundaries with completeness and no gaps in the resulting binary image. In all the other cases pseudo-edges or broken tree boundaries appear that affect the result,

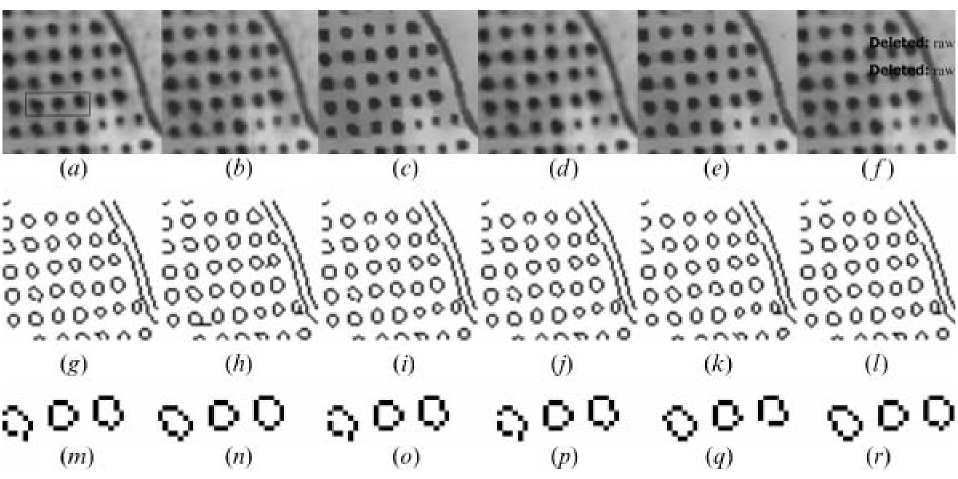

Figure 1. Improving automatic olive tree extraction by applying the developed processing scheme to an IKONOS PAN 1-m ground resolution image. First row: (*a*) original image, (*b*) ML filtering result with scale 3, (*c*) PM filtering result, (*d*) ALM filtering result, (*e*) BS filtering result and (*f*) developed scheme filtering result. Second row: resulting image after applying the Canny edge detector to the (*g*) original image, (*h*) ML result, (*i*) PM result, (*j*) ALM result, (*k*) BS result and (*l*) developed scheme's result. Third row: zoom on the rectangular part (specified in (*a*)) of the resulting image from the second row.

since the incompetence in olive tree boundary extraction leads to unconnected feature components and additional post-processing operations with uncertain success.

3.2 *Segmentation*

The developed filtering technique was also evaluated as a pre-processing operator for image segmentation and more specifically for improving watershed segmentation. In general, the morphological watershed transform creates a tessellation of the image domain in several small regions by considering the image values as intensity levels (planes) in a topographical landscape. By simulating rainfall, the domain is grouped in catchment basins, regions in which the water drains from all points to the same local intensity minimum. Naturally this method is very sensitive to small variations of the image magnitude and consequently the number of generated regions is undesirably large. To overcome this problem of identifying exhaustively many segments there have been efforts in recent years to reduce the complexity of the tessellation by: (i) region merging techniques (Haris *et al.* 1998), (ii) marker-controlled watershed flows, where the design of robust marker detection techniques involves the use of knowledge specific to the images under study; not only object markers, but also background markers need to be extracted (Meyer and Maragos 1999) and (iii) studying the evolution of the catchment basins in Gaussian scale-space (Gauch 1999). Such techniques can generate unpredictable results and depend to a large extent on user interaction and the quality of the initial partition (Droske *et al.* 2000).

The goal here was to use the developed multiscale filtering tool to decrease the heterogeneity of the initial image (in spectral and spatial domains) so that in the resulting segmentation adjacent pixels appear more aggregated (the extent of which is controlled by the scale parameters t and i).

In figure 2 the efficiency of the developed filtering tool, during the pre-processing step of image simplification, is demonstrated for solving over-segmentation problems of the watershed transformation. The developed scheme by simplifying the image and removing irrelevant image structures deals with watershed over-segmentation problems, since the algorithm not only enlarged but also created new flat (smooth) image zones. Segmentation quality can be compared quantitatively in terms of the number of regions obtained after using the developed algorithm. In all cases in figure 2 the developed scheme effectively decreased the number of output segments (over a 10% decrease was achieved). In addition the achieved edge preserving, geometric driven, image simplification forced the merging of pixels that belong to the same categories/objects (figure 2(*a*), in the background grass area segments were merged; figure 2(*b*), segments inside the ship and dock areas were merged; figure 2(*c*), segments in boulevards and in rows of trees were merged) and furthermore this was accomplished (i) with no need for post-processing-like region merging techniques and (ii) without the use of any background or foreground markers, the selection of which is not at all a trivial matter.

4. Conclusion and future perspectives

The proposed processing scheme introduced an advanced nonlinear scale space representation by a combination of ADF and ML, towards a superior

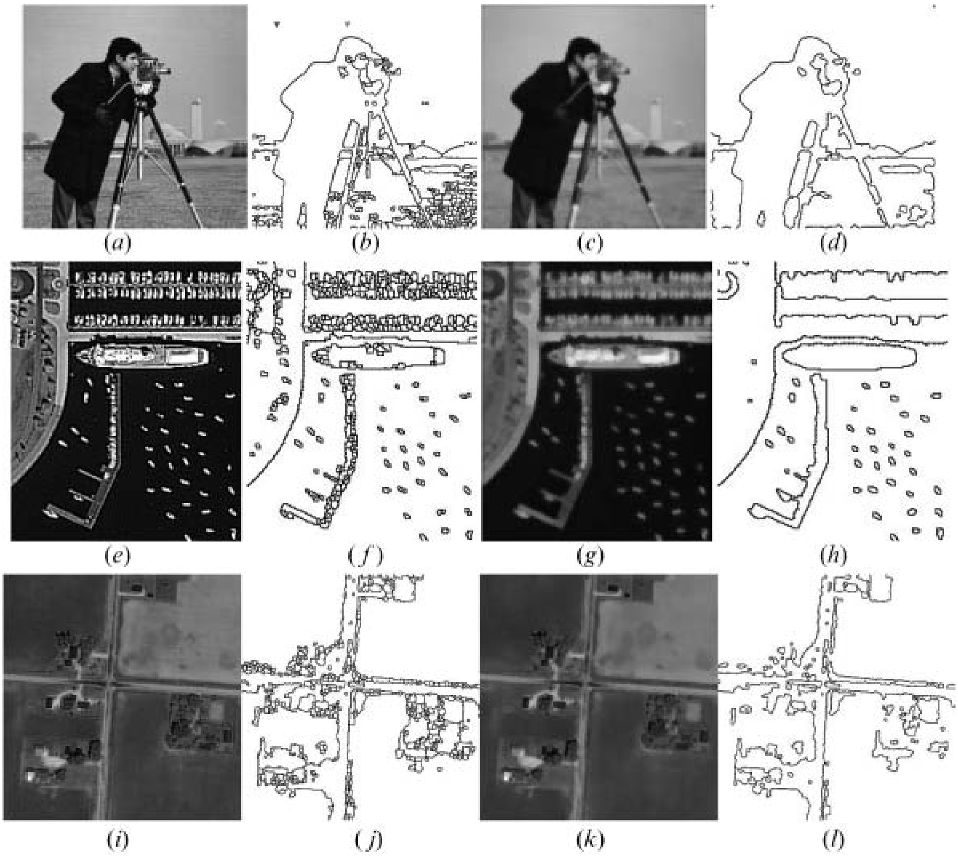

Figure 2. Segmentation based on the developed processing scheme: (*a*) original image, (*b*) watershed segmentation on the original image (336 segments), (*c*) resulting image after applying ADF with 130 iterations and ML with scale 4, (*d*) watershed segmentation to processed image (38 segments), (*e*) original image, (*f*) watershed segmentation on the original image (398 segments), (*g*) resulting image after applying ADF with 130 iterations and ML with scale 4, (*h*) watershed segmentation to the processed image (55 segments), (*i*) original image, (*j*) watershed segmentation on the original image (512 segments), (*k*) resulting image after applying ADF with 70 iterations and ML with scale 2, (*l*) watershed segmentation to the processed image (124 segments).

(advanced) image simplification and smoothing. Experimental results on automatic olive tree extraction and watershed segmentation showed its effectiveness as a pre-processing tool for edge detection and segmentation from remote sensing images.

Our interest has focused on panchromatic high spatial resolution satellite sensor data processing but the developed scheme can also be applied to colour and multidimensional image data by processing each channel separately. Finally, the tuning of the two scale parameters (t and i) is an open matter, but has to be regarded as an object-oriented selection task during object extraction.

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