ACTIVE CONTOUR MODEL TO DETECT LINEAR FEATURES IN SATELLITE IMAGES

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ABSTRACT:

Active contour models are used extensively in image processing applications, including edge detection, shape modelling, segmentation and in general to detect object boundaries. They are curves defined in the image domain that can move under the influence of internal forces within the curve itself and external forces derived from the image data. Many versions and improvements have been proposed since then, in an effort to improve on several aspects of the original finite difference implementation.
We present preliminary results of a wavelet based active contour model for detecting linear features in satellite images The method combines multi-scale decomposition and edge detection in a fast-converging iterative scheme. As an application, coastline retrieval from a SAR image is illustrated.

1. INTRODUCTION

Satellite images can hardly be automatically segmented, due to their inherent complexity. Low signal-to-noise ratio, undesired images features and other factors further complicate this issue. Manual and semi-automatic tracking of images is still the mainstream method for obtaining good segmentations of complicated images. Many algorithms have been proposed to extract features from satellite images.
The subject of the present study is a group of high level segmentation models, the so called active contour models for detecting linear features.
Active contour models, also known as snakes, are used extensively in image processing applications, including edge detection, shape modeling, medical image-analysis, to detect object boundaries. Snakes are curves defined in the image domain that can move under the influence of internal forces within the curve itself and external forces derived from the image data. The internal and external forces are defined so that the snake will eventually conform to an object boundary or some other desired image feature.
Problems associated with initialization and poor convergence to concave boundaries, however, have hitherto limited their use.
They were first proposed in 1987 by Kass, Witkin and Terzopoulos. Many versions and improvements have been proposed since then, in an effort to improve on several aspects of the original finite difference implementation.
In fact the original snake model presents a number of limitations. First, the initial contour should be sufficiently close to the object, to prevent converge to wrong results. Second, the performance of the snake depends on the number of control points, which is usually fixed. Besides, the method is unable to extract the multiple-objects contours and runs into difficulties when facing concave boundaries.
In this paper we apply an algorithm which uses a modified version of the active countour model which features a new class of external forces to addresses the problems listed above.

Generally, the most common method used to detect an edge contour in an image is to set the external energies as the negative modulus of the gray level gradient of the image.
We define this energy as the negative of the modulus of a wavelet transform of the image. In particular we utilize wavelet transforms to obtain a filtered image at a certain scale. The desired contour is accordingly identified, through the active contour model, working on the filtered image. Then, the obtained contour is taken as the initial position of the snake on a wavelet-filtered image corresponding to a more accurate scale. The process ends when the scale (detail) level of the original image has been reached.
The algorithm has been applied to identify different features and detect linear characteristics in satellite images.

2. SNAKE MODEL

A snake (Kass et al., 1987) is a parametric curve defined in the image domain which is initialized manually by a set of control points, lying on an open or closed curve.

$$v(s) = \left(x(s), y(s)\right) \qquad s \in [0,1] \tag{1}$$

Associated to a snake is an *energy function* which is used to move the snake across the image. For each control point, the energy is recalculated for all points in its neighborhood and the point that minimizes this energy function is used to update the control point. Once the update procedure settles, one has hopefully detected a feature of interest (edge), which can be reconstructed by interpolation among the control points.
The energy functional to be minimized is defined as

$$E_{snake} = \int_0^1 \left\{E_{\text{int}}\left(v(s)\right) + E_{image}\left(v(s)\right)\right\} ds \tag{2}$$

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where E_{int} represent the internal deformation energy defined as

$$E_{\text{int}} = \frac{1}{2}\int_0^1 \left(\alpha(s)\left|v^{'}(s)\right|^2 + \beta(s)\left|v^{''}(s)\right|^2 \right) ds \tag{3}$$

where α and β are weighting parameters that control the snake's tension and rigidity, respectively, and $v^{'}(s)$ and $v^{''}(s)$ denote the first and second derivatives of $v(s)$ with respect to s.

The second term in (2) is an external image energy. Typical forms of image energy are

$$E^1_{image} = -\left|\nabla I(x,y)\right|^2, \tag{4}$$

$$E^2_{image} = I(x,y). \tag{5}$$

In (4), $I(x,y)$ is a grey-level function (intensity); in (5), the intensity is a binary function (black and white, line-art image).

A snake that minimizes E must satisfy the Euler equation

$$\alpha v^{''}(s) - \beta v^{'''}(s) - \nabla E_{image} = 0, \tag{6}$$

which can be viewed as a force balance equation

$$F_{\text{int}} + F_{image} = 0. \tag{7}$$

The internal force F_{int} prevents stretching and bending, while the external force F_{image} pull the snake toward the desired image edges.

To find a solution to (6), the snake is made dynamic by treating v as function of time t as well as s, $v(s,t)$.

A solution is obtained by seeking the snake position for which the velocity, defined by

$$v_t(s,t) = \alpha v^{''}(s,t) - \beta v^{'''}(s,t) - \nabla E_{image}, \tag{8}$$

vanishes.

3. NUMERICAL IMPLEMENTATION

In the original model (Kass, 1987) a parametric contour representation is used to implement a semi-implicit integration scheme for discretizing the law of motion.

Several authors have proposed different representations (Menet at al., 1993) including the use of finite element models (Cohen et al., 1992), subdivision curves (Hug et al., 1999) and analytical curve models (Metaxas and Terzopoulos, 1991) which work better to determine different *features* on the image. Various formulations of the image energy have also been proposed to improve the original model, including the "Balloon" force field (Cohen, 1991) and the Gradient Vector Flow force field (Xu and Prince, 1998).

In this paper, we use an algorithm based on a hierarchical filtering procedure, known as the *scale-space continuation method* (Within, 1983; Leymarie and Levine, 1993), subsequently generalized to fit the *wavelet-based snake* (Liu and Hwang, 1992).

The idea of the scale-space continuation method (Leymarie and Levine, 1993) is to calculate the snake in a coarsely smoothed image; then the result at the coarse scale is used as an initial contour on a finer image and so on, until the native image resolution is reached. The original image is filtered through a family of Gaussian filters with different resolutions. Then, a differentiating filter, such as the Sobel filter, is applied to these Gaussian filtered images to produce approximations of the gradients of the Gaussian smoothed image.

The next advance was to implement the gradient-based scale-space continuation method by means of a wavelet transform (Liu and Hwang, 1992). In this connection it has been shown (Mallat and Zhong, 1992) that the first derivatives of a family of Gaussian filters are equivalent to the corresponding wavelet transform coefficients multiplied by a scaling constant.

Let the family Gaussian filters be suitably chosen so as to satisfy the 2-D dilation equation

$$\theta_s(x,y) = \frac{1}{s^2}\theta\left(\frac{x}{s},\frac{y}{s}\right), \tag{9}$$

the 2-D wavelet functions are defined, in the x- and y-direction as

$$\psi^1(x,y) = \frac{\partial\theta(x,y)}{\partial x}, \qquad \psi^2(x,y) = \frac{\partial\theta(x,y)}{\partial y}, \tag{10}$$

then the wavelet transform of a (gray-scale) image $I(x,y)$ in the x- and y-direction at scale s are

$$W^1_s I(x,y) = I * \psi^1_s(x,y), \qquad W^2_s I(x,y) = I * \psi^2_s(x,y). \tag{11}$$

It can be shown (Mallat and Zhong, 1992) that

$$\begin{pmatrix} W^1_s I(x,y) \\ W^2_s I(x,y) \end{pmatrix} = s\nabla(I * \theta_s)(x,y) \tag{12}$$

therefore, the above equation implies that applying wavelet transform is equivalent to applying both smoothing and gradient operations.

It has been shown (Mallat, 1998) that fast implementation of (12) can be achieved when s is an integer power of 2 by filtering alternatively through a low-pass filter (L) and a high-pass filter (H).
Then, the external energy at scale s is defined as the negative of the modulus of wavelet transform at scale s

$$E_{image}(x,y) = E^{s}_{ext}(x,y) = -\sqrt{\left|W^{1}_{s} I(x,y)\right|^{2} + \left|W^{2}_{s} I(x,y)\right|^{2}} \quad (13)$$

The above definition of external energy together with the continuation method in the wavelet domain represents a generalized version of the gradient-based scale-space continuation method.
We employ this wavelet- based snake model in our experiments on satellite images. The flow chart of utilized model is shown in Figure 1.

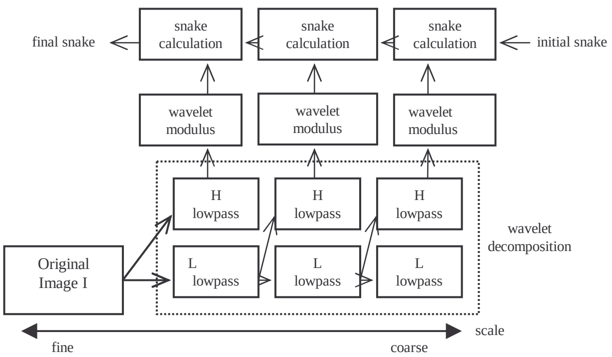

Figure 1. Flow chart of the wavelet-based active contour model

4. TESTS AND RESULTS

The wavelet-based active contour model has been tested on satellite images to determine different features and detect linear characteristics. This model has been applied on SAR images first, and then on high resolution images.
In this paper we present tests carried out on a SAR image of Italy aimed at the detection of the coastline.
Coastline detection is generally based on the comparison with existing cartography, which is relative to temporarily distant periods and it would therefore demand a repeated updating not realistically feasible.
The use of satellite images represents, potentially, a faster and flexible alternative. In particular, these images allow to cover wide scales, at unprecedented uniform accuracy levels.
Edge detection in SAR images is made difficult by the presence of speckle, and std. methods developed for optical images are generally applied only after a process of speckle reduction.
The wavelet-based active contour model combine wavelet decomposition (Dohono, 1995) and edge detection in a single procedure.
With reference to the flow chart in Figure 1, the first operation consists in filtering through a low-pass filter and a high-pass filter the original image. We shall refer as an illustration to the SAR image acquired by the ERS-2 Satellite on 25 June 1995 of gulf of Salerno (Italy).

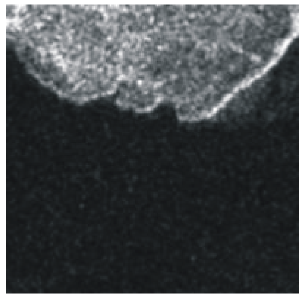

Figure 2. Original image

After the low-pass and high-pass filters are applied, the results are displayed in the following figures, which refer to three different scales of increasing accuracy

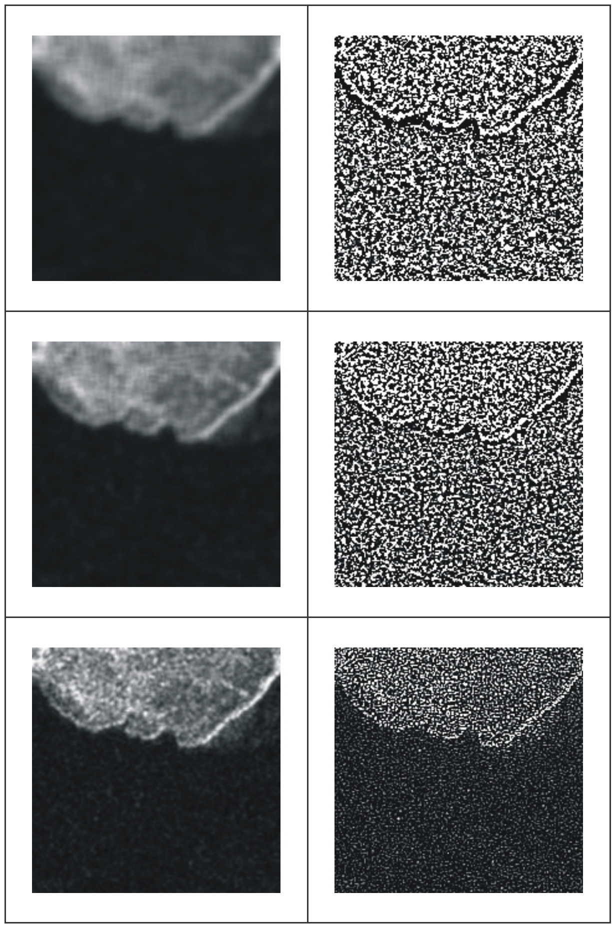

Figure 3. Low-pass and high-pass filters applied to the original image at three different scales of increasing accuracy.

We next calculate the wavelet modulus by using (13) at all scales. At each step, the snake is obtained. The resulting curve is used as an initial guess for the snake at the next finer scale. The process is repeated until the finest scale available in the original image is reached .

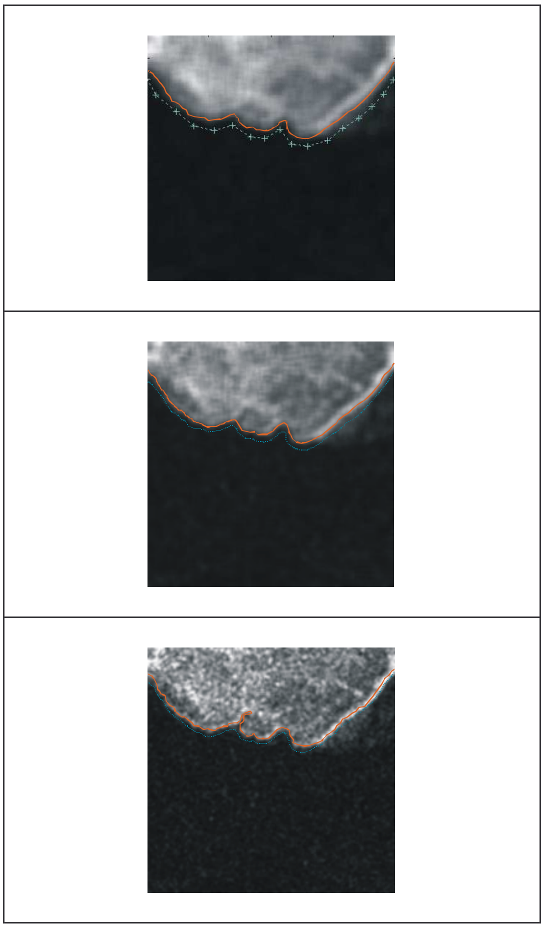

Figure 4. Convergence of the snake at increasing scale

The whole process is rapidly convergent. The final result is shown below. Comparison with ground truth is currently under way.

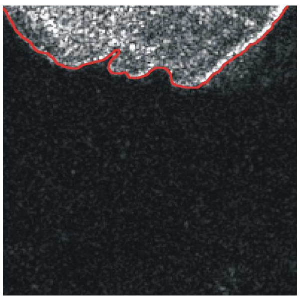

Figure 5. Snake at original image

5. CONCLUSION

We have employed an algorithm which utilizes a modified version of the active contour model, using a class of external forces defined by the negative of the modulus of wavelet transform of the image. The wavelet-based active contour model combine wavelet decomposition and edge detection in a single procedure. It has been applied to SAR satellite images to determine the coastline. Obtained results are encouraging, and further tests are in progress.

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