Image Segmentation Using Active Contour Model and Level Set Method Applied to Detect Oil Spills

M. Airouche[(1)], L. Bentabet[(2)] and M. Zelmat[(1)]

Abstract— **In this paper we explore image segmentation using active contours model to detect oil spills. A partial differential equation based level set method, which represents the spill surface as an implicit propagation interface, is used. Starting from an initial estimation with priori information, the level set method creates a set of speed functions to detect the position of the propagation interface. Specifically, the image intensity gradient and the curvature are utilized together to determine the speed and direction of the propagation. This allows the front interface to propagate naturally with topological changes, significant protrusions and narrow regions, giving rise to stable and smooth boundaries that discriminate oil spills from the surrounding water. The proposed method has been illustrated by experiments to detect oil spills in real images. Its advantages over the traditional image segmentation approaches have also been demonstrated.**

***Index Terms*— Active contours, Image segmentation, Level sets.**

I. Introduction

Image segmentation consists of partitioning an image into homogeneous regions that share some common proprieties. There are two main approaches in image segmentation: edge- and region-based. Edge-based segmentation looks for discontinuities in the intensity of an image. Region-based segmentation looks for uniformity within a sub-region, based on a desired property, e.g. intensity, color, and texture. Automatic interpretation of images is a very difficult problem in computer vision. Several methods are developed in last decade to improve the segmentation performance in computer vision. A promising mathematical framework, based on variational models and partial differential equations, have been investigated to solve the image segmentation problem. This approach benefits from well-established mathematical theories that allow people to analyze, understand and extend segmentation methods. In this paper, a variational formulation is considered to the segmentation using active contours models. Active contours models are used to detect objects in a given image using techniques of curve evolution. The basic idea is, starting with an initial curve *C*, to deform the curve to the boundary of the object, under some constraints from the image. The development of active contour methods to simulate curve evolution for segmentation has come from the efforts of many scientists and over a decade of research. Methods to evolve these contours were introduced to computer vision by Kass, Witkin and Terzoupolus [6] and then reformulated in the context of PDE-driven surfaces by Caselles, Kimmel and Sapiro in [7] using the level set framework. Geometric active contour model was the first level set implemented active contour model for the image segmentation problem. It was simultaneously proposed by Caselles, Kimmel and Sapiro in [7] and by malladi et al [8]. This model is based on the theory of curve evolution and geometric flows. Geodesic active contour model was proposed by Caselles et al. [9] after the geometric active contour model. This geodesic approach for image segmentation allows to connect classical "snakes" based on energy minimization and geometric active contours based on the theory of curve evolution. In order to improve the segmentation performance, the integration of edge- and region based information sources using active contours has been proposed by a few authors. Geodesic active region is a supervised active contour model, proposed by Paragios [10]. The active contour model without edges was proposed by Chan and Vese [11]. The proposed models can identify individual segments in images with multiple segments and junctions, as compared with the initial model [11], where the detected objects were belonging to the same segment.

Our approach is based in the active contour model with the integration of adaptive region information to obtain a robust segmentation model. This method is applied to segmenting images to improve oil spill detection in marine environment. In the recent years, marine pollution has become a major issue due to the increasing number of illicit discharges and accidents of big oil tankers. Spillage of oil in coastal waters can be a catastrophic event. The potential damage to the environment and economy of the area at stake requires that agencies be prepared to rapidly detect, monitor, and clean up any large spill. The complications involved in detecting oil spills are due to varying wind and sea surface conditions. In the last decade, imaging systems have been widely used in remote sensing to improve methods of oil spills detection. We use our approach to detect oil spills in real images obtained with these imaging systems.

Manuscript received March 2, 2009.

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II. ACTIVE CONTOURS MODEL

Segmentation using active contours model (*Snakes)* was introduced by Kass *et al* [6]. The idea behind active contours, or deformable models, for image segmentation is quite simple. The user specifies an initial guess for the contour, which is then moved by image driven forces to the boundaries of the desired objects. In such models, two types of forces are considered - the internal forces, defined within the curve, are designed to keep the model smooth during the deformation process, while the external forces, which are computed from the underlying image data, are defined to move the model toward an object boundary or other desired features within the image. One way of describing this curve is by using an explicit parametric form, which is the approach used in snakes. This causes difficulties when the curves have to undergo splitting or merging, during their evolution to the desired shape. To address this difficulty, the implicit active contour approach, instead of explicitly following the moving interface itself, takes the original interface and embeds it in higher dimensional scalar function, defined over the entire image. The use of level set method has provided more flexibility and convenience in the implementation of active contours.

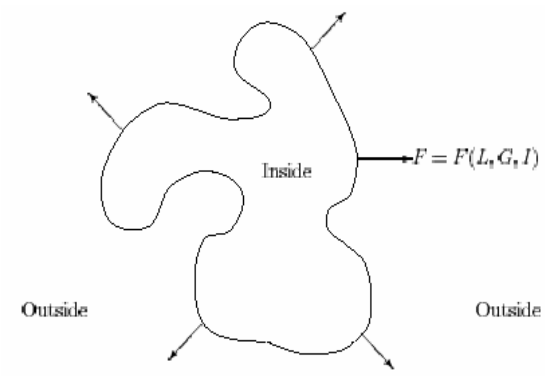


Fig. 1: Contour initialisation

III. LEVEL SETS METHOD

The level set method was first introduced by Osher and Sethian [13]. The level set method is a numerical and theoretical tool for propagating interfaces. The basic idea is to start with a closed curve in 2D or a surface in 3D and allow the curve to move perpendicular to itself at a prescribed speed. In image processing the level set method is most frequently used as a segmentation tool through propagation of a contour by using the properties of the image. One of the first applications was to detect edges in an image [14], but in more recent applications textures, shapes, colors etc can be detected. In the level set method, an interface C is represented implicitly as a level set of a function ϕ, called level set function, of higher dimension. The geometric characteristics and the motion of the front are computed with this level set function. The interface is now represented implicitly as the zero-th level set (or contour) of this scalar function. Over the rest of the image space, this level set function is defined as the signed distance function from the zero-th level set. Specifically, given a closed curve C, the function is zero if the pixel lies on the curve itself, otherwise, it is the signed minimum distance from the pixel to the curve. By convention, the distance is regarded as negative for pixels outside C and positive for pixels inside C. The level set function ϕ of the closed front C is defined as follows, [13]:

$$\phi(x, y) = \pm d((x, y), C) \quad (1)$$

Where $d((x, y), C)$ is the distance from point (x, y) to the contour C, and the sign plus or minus are chosen if the point (x, y) is inside or outside of interface C.

The interface is now represented implicitly as the zero-th level set (or contour) of this scalar function :

$$C = \{(x, y) / \phi(x, y) = 0\} \quad (2)$$

Such an implicit representation has numerous advantages over a parametrical approach. The most striking example is topological changes occurring during the propagation, typically when two flames burn together the evolving interfaces merge into one single propagating front as show fig. 2.

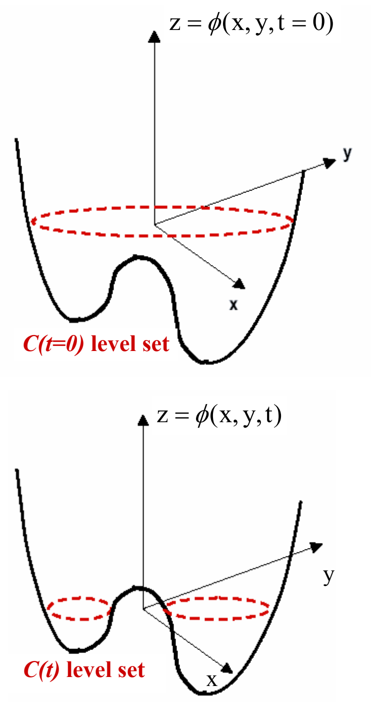


Fig. 2: Curve Evolution

The function ϕ, which varies with space and time (that is, $\phi = \phi((x, y), t)$ in two dimensions) is then evolved using a partial differential equation (PDE), containing terms that are either hyperbolic or parabolic in nature.

In order to illustrate the origins of this PDE, we next consider the evolution of the function ϕ as it evolves in a direction

ISBN: 978-988-17012-5-1

normal to itself with a known speed F. Here, the normal is oriented with respect to an outside and an inside. The idea of the level set method is to consider the evolving interface $C((x,y),t)$ as the set of zero-values of the function ϕ ($\phi(C((x,y),t),t)=0$).

We can write :

$$\frac{\partial\phi(x,y)}{\partial t}+\nabla\phi\frac{\partial C((x,y),t)}{\partial t}=0 \quad (3)$$

We find then the equation of level set introduced by Osher and Sethian [13] f or ϕ:

$$\frac{\partial\phi(x,y)}{\partial t}=F|\nabla\phi| \quad (4)$$

Where F denotes a constant speed term to push or pull the contour.

A particular case is the motion by mean curvature, when $F=div(\nabla\phi/\|\nabla\phi\|)$ is the curvature of the level-curve of ϕ passing through (x,y).

A geometric active contour model based on the mean curvature motion is given by the following evolution equation [7] :

$$\frac{\partial\phi(x,y)}{\partial t}=|\nabla\phi(x,y)|(\varepsilon\kappa(\phi(x,y))+\nu) \quad (5)$$

The constant ν is a correction term, which is a chosen so that the quantity $(\nu+\varepsilon\kappa(\phi(x,y)))$ remains always positive. This constant may be interpreted as a force pushing the curve toward the object, when the curvature becomes null or negative. Also, $\nu>0$ is a constraint on the area inside the curve, increasing the propagation speed.

Where κ denotes the mean curvature of the level set function given by :

$$k(\phi(x,y))=div\left(\frac{\nabla\phi}{\|\nabla\phi\|}\right) \quad (6)$$

$$k(\phi(x,y))=\frac{\phi_{xx}\phi_y^2-2\phi_x\phi_y\phi_{xy}+\phi_{yy}\phi_x^2}{\left(\phi_x^2+\phi_y^2\right)^{3/2}} \quad (7)$$

Where ϕ_x and ϕ_{xx} denote the first- and second-order partial derivatives of $\phi(x,y)$ respect to *x*, and ϕ_y and ϕ_{yy} denote the same respect to *y*. The role of the curvature term is to control the regularity of the contours as the internal energy term does in the classic snakes model, and ε controls the balance between the regularity and robustness of the contour evolution.

Adding an additional term, called stopping function, to the speed function in the geometric active contour model proposed by Caselles et al. [7] give :

$$\frac{\partial\phi(x,y)}{\partial t}=g(I(x,y))(\varepsilon\kappa(\phi(x,y))+\nu)|\nabla\phi(x,y)| \quad (8)$$

Where $g(I(x,y))$ denotes the stopping function, i.e. a positive and decreasing function of the image gradient. A simple example of the stopping function is given by :

$$g(I(x,y))=\frac{1}{1+|\nabla I(x,y)|} \quad (9)$$

The contours move in the normal direction with a speed of $g(I(x,y))(\nu+\varepsilon\kappa(\phi(x,y)))$, and therefore stops on the edges, where g(·) vanishes. The curvature term κ maintains the regularity of the contours, while the constant term ν accelerates and keeps the contour evolution by minimizing the enclosed area [7].

Geodesic active contour model was proposed by Caselles et al [9]. Solving this geodesic problem is equivalent to searching for the steady state of the level set evolution equation [9] given by :

$$\frac{\partial\phi(x,y)}{\partial t}=g(I(x,y))(\kappa(\phi(x,y))+\nu)|\nabla\phi(x,y)| +\nabla g(I(x,y)).\nabla\phi(x,y) \quad (10)$$

Piecewise-constant active contour model was proposed by Chan and Vese [12] using the Mumford-Shah segmentation model. Piecewise-constant active contour model moves deformable contours minimizing energy function instead of searching edges. A constant approximates the statistical information of image intensity within a subset, and a set of constants, i.e. a piecewise-constant, approximate the statistics of image intensity along the entire domain of an image. The energy function measures the difference between the piecewise-constant and the actual image intensity at every image pixel. The level set evolution equation is given by :

$$\frac{\partial\phi(x,y)}{\partial t}=\delta_\varepsilon(\phi(x,y))\begin{bmatrix}\nu\kappa(\phi(x,y)-\\ \{(I(x,y)-\mu_1)^2-(I(x,y)-\mu_0)^2\}\end{bmatrix} \quad (11)$$

Where μ_0 and μ_1 respectively denote the mean of the image intensity within the two subsets, i.e. the outside and inside of contours. The final partitioned image can be represented as a set of piecewise-constants, where each subset is represented as a constant. This method has shown the fastest convergence speed among region-based active contours due to the simple representation.

IV. Numerical Implementation of the Level Set Method

The level set method as initially proposed to solves the level set equation on the entire domain of ϕ. However, for most applications, the method is used to track the motion of a particular interface, or level set, of ϕ with isovalue zero. Therefore, the computations can be restricted to a neighborhood around the zero crossing, with the same results as solving the equation on the entire domain. Using Narrow band schemes, the computational cost is proportional to the size of the interface. This is makes a considerable difference for the running time, especially when propagating surfaces in three dimensions or higher. Fig. 3 shows the placement of the narrow band around the familiar initial front.

Only the values of ϕ within the narrow band are updated. Values of ϕ at grid point on the boundary of the narrow band are frozen. When the front moves near the edges of the tube boundary, the calculation is stopped, and a new tube is built with zero level set interface boundary at the center. This rebuilding process is known as “re initialisation”.

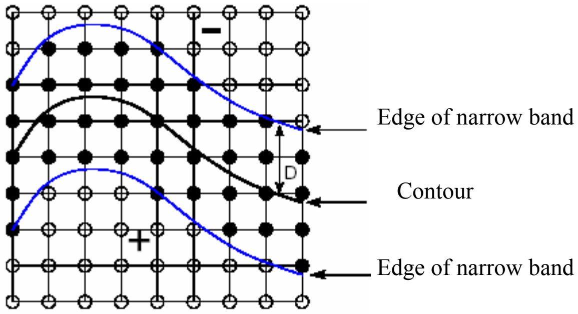


Fig. 3: Illustration of narrow band

The narrow band method consists of the following loop:

- Tag alive point in narrow band
- Build land mines to indicate near edge.
- Initialize far away points outside narrow band with large positive (negative) value if values are outsid (inside)the front itself
- Solve level set equation until land mine hit
- Rebuild and loop

The first term of the right hand side of equation (10) is a convection term. The second term of the right hand side of equation (10) is a contour smoothing term based on the curvature of level sets of ϕ. To discretize the equation in ϕ, we use a finite differences implicit scheme. The finite differences are :

$$D_{ij}^{+x} = \frac{\phi_{i+1,j} - \phi i, j}{\Delta x} \quad (12)$$

$$D_{ij}^{-x} = \frac{\phi_{i,j} - \phi i - 1, j}{\Delta x} \quad (13)$$

$$D_{ij}^{0x} = \frac{\phi_{i+1,j} - \phi i - 1, j}{\Delta x} \quad (14)$$

Then, we compute the level set function by the following discretization and linearization :

$$\phi_{i,j}^{n+1} = \phi_{i,j}^{n} + \Delta t\left[\max(F_{ij},0)\nabla^{+} + \min(F_{ij},0)\nabla^{-}\right] \quad (15)$$

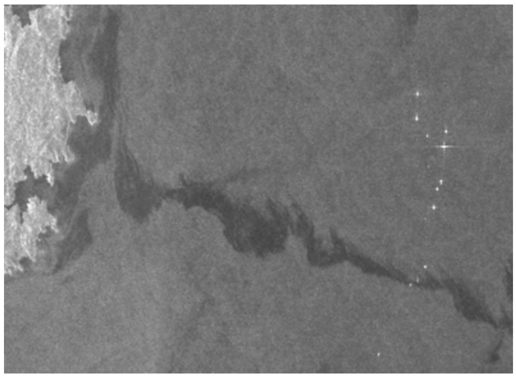
Where

$$\nabla^{+} = \begin{bmatrix} \max(D_{ij}^{-x},0)^2 + \min(D_{ij}^{+x},0)^2 + \\ \max(D_{ij}^{-y},0)^2 + \min(D_{ij}^{+y},0)^2 \end{bmatrix}$$

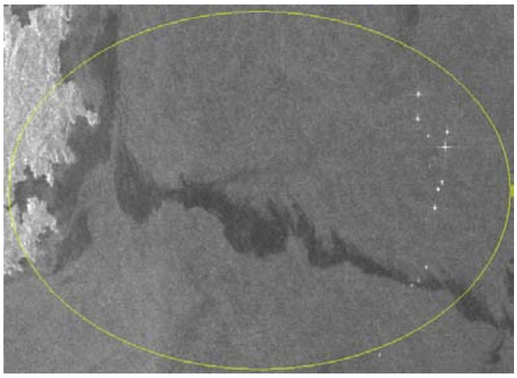
and $\nabla^{-} = \begin{bmatrix} \max(D_{ij}^{+x},0)^2 + \min(D_{ij}^{-x},0)^2 + \\ \max(D_{ij}^{+y},0)^2 + \min(D_{ij}^{-y},0)^2 \end{bmatrix}$

V. Results

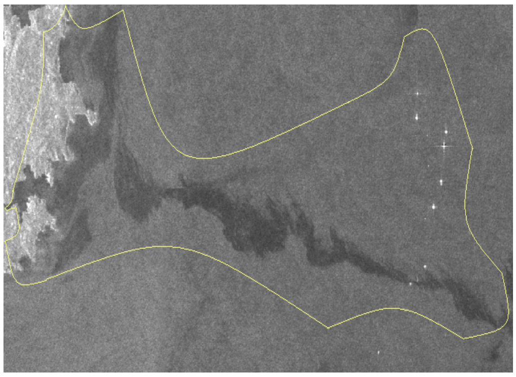
Fig. 4 and fig. 5 illustrate the results of application of our method in real images obtained with satellite imaging systems in order to detect oil spills and validate our method.



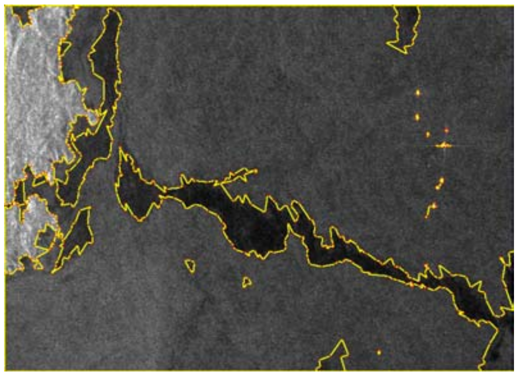
(a)



(b)



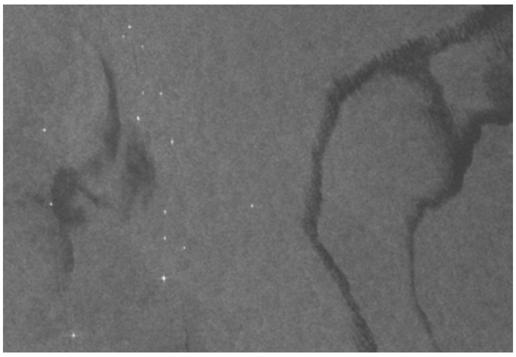
(c)



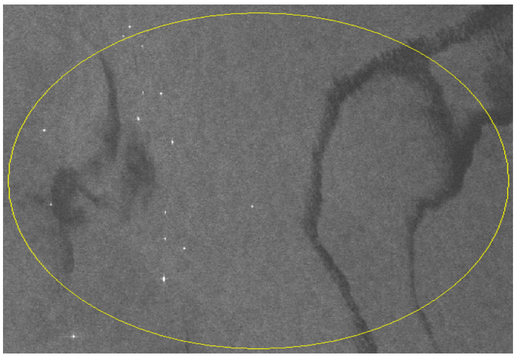
(d)

Fig. 4: image segmentation (a) original image, (b) initial curve, (c) intermediate curve, (d) final segmentation

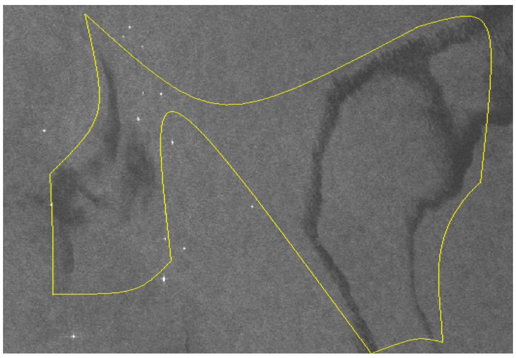
ISBN: 978-988-17012-5-1



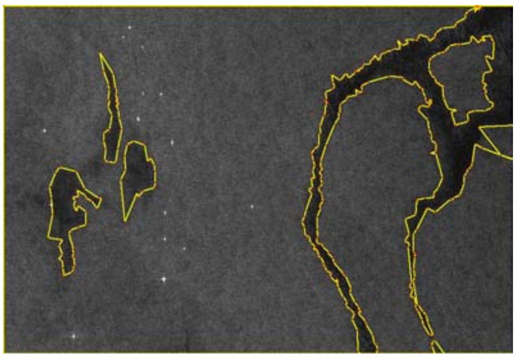
(a)



(b)



(c)



(d)

Figure 5: image segmentation (a) original image, (b) initial curve, (c) intermediate curve, (d) final segmentation

VI. CONCLUSION

The proposed image segmentation method uses the framework of active contours. As active contours always provide continuous boundaries of sub-regions, they can produce more reasonable segmentation results than traditional segmentation methods, and consequently improve the final results of image analysis. The mathematical implementation of the proposed active contour models is accomplished using level set method. By presenting contours as a level of a topological function, we can merge multiple contours into one contour, or can split a contour into multiple contours, providing a good flexibility in the use of active contours. The proposed image segmentation method permits to improve oil spills detection in real satellite images.

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