Experimenting level set-based snakes for contour segmentation in radar imagery*

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ABSTRACT

The aim of this work is to explore the applicability of a relatively new snakes formulation called geometric snakes, for robust contour segmentation in radar images. In particular, we are looking for clear experimental indicators regarding the usefulness of such tool for radar imagery. In this work, we mainly concentrate on various contour segmentation problems in airborne and spaceborne SAR images (swath and inverse mode). As an example, we study the segmentation of coastlines and ship targets. We observe that the dynamical and adaptive properties of geometric contours is better suited to determine the morphological properties of the contours. For high-resolution radar images of ships, the underlying motivation is that these properties could help providing robust extraction of ship structures for automatic ship classification.

Keywords: Active contours, Snakes, Edge detection, Segmentation, Radar imagery

1. INTRODUCTION

In recent years, works toward automatic segmentation of images have made significant progresses. Application range from detection of forms to visual tracking and shape modeling. Among the different approaches to image segmentation, the detection of contours is a very important one, and it can be used as a first step in a chain of processes applied to an image. The main difficulties with contour segmentation are often related to the presence of noise in the image or to low contrast edges. An efficient method to recover edges in an image with such characteristics is based on active contours or snakes.

The classical formulation of snakes involves a simple paradigm based on the minimization of an energy function. Typically, a parametric curve $C(\gamma)$ is constructed in a 2D-image (the pixel coordinates $(x,y)\rightarrow\gamma \subset [0,1]$ describes the curve) with an associated energy $E(C)$ that is assumed to take the form

$$E(C) = E_{\text{int}}(C) + V(C)$$

The term $E_{int}(C)$ is the internal energy of the curve and is independent of the underlying image. The internal energy essentially weights the rigidity and tension of the curve and control in some sense the inherent smoothness of the curve. The potential $V(C)$ depends on the image (i.e. the pixel intensity $I(x,y)$ and local variations) which we take to be gray scale, that is $I(x,y) \subset [0,N_G]$, with N_G the maximal gray value (usually 255). To detect a contour, we let the snake to be attracted to the local minimum of the potential which we could take for example as $V(C)\propto|\nabla G*I(x,y)|$ where G is a Gaussian filter. The contour is then the curve minimizing this energy function $E(C)$ for a given set of parameters.

Finding the optimal contour is typically done by adding dynamics to the snake. If we add kinetic energy to the curve, then using the Lagrangian formulation for $E(C)$, we can minimize the action and find a corresponding dynamical equation of motion. One then starts with an initial snake and let it evolve until some suitable conditions are satisfied, i.e. a local minimum of the potential.

The main problem is that there can be (and there usually is) more than one minimum for $V(C)$. Typically, there are local minima associated with noisy points, which are punctual in the image (having a small area). The advantage of snake formulations is that since the dynamics is controlled by the image, but also by a snake tension, we can adjust the different energies associated with a configuration such that the local minimum will be avoided and the snake will asymptotically flow

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towards the global minimum. In some sense, we can think of a snake as an elastic; when a local tension builds up caused by a local impurity, then it eventually steps over the impurity. If, on the other hand, the obstruction is more macroscopic, then it stops there.

This classical approach has been supplanted by geometric snakes for many reasons, one of them is that the solution is not very stable, and the initial snake needs to be close to the contour to detect. Moreover it does not allow for splitting or merging of snakes which makes the approach inefficient when there are topologically non-trivial contours in an image (for example there can be more than one ship to segment in a given image or islands near coastlines).

Geometric snakes to be used here are based on a level set representation of a curve and can be seen as curvature dependent propagating fronts under the influence of a scalar potential. Level set-based snakes have been used to study MRI, ultrasound and CT images, where the results have been promising, even for noisy images [1]. Applications of level set-based snakes to other type of imagery and problem are also the object of active research. For instance, interest to level set-based snakes to microscopic imagery is that it might provide a robust solution to the problem of cell segmentation in noisy and/or non-uniform backgrounds. In particular, we have made some preliminary tests showing that level-set snakes might allow robust segmentation of skin tumors, even in the presence of hair. Similar motivations underlie the segmentation of objects in noisy coherent imaging like radar images.

In the next Section, we provide the details of the level set-based snake algorithm and the specifics related to radar images. In Section 3, we report about the behavior of level set-based snakes as well as the effect of the various parameters using an artificially degraded synthetic image. In the last Section, we provide examples of contour segmentation on real radar images.

2. GEOMETRIC SNAKE AND LEVEL SETS

The geometric formulation of snakes is based on Euclidean curve shortening equations. Essentially, these equations govern the dynamics of a curve $C(\gamma,t)$ through

$$\frac{\partial C}{\partial t} = R\overrightarrow{N}$$

where R is the scalar curvature and N the inward unit normal to the curve. This equation is such that the flow of the Euclidean curve maximizes the shortening of the curve perimeter in time. Another useful property is that the evolution is such that the curve converges to round points without developing singularities as it flows. Physically, we can think of this equation as reducing the protuberances of the curve faster than it does for the uniform parts while shrinking the perimeter.

This approach is very different than the classical formulation we sketched in Section 1. Here we start from the dynamic of a shrinking curve and, as it will become clear in the following, add terms dependent on the image to control how the contour behaves. Before we do this, we will reformulate everything by using a slightly different viewpoint. As presented above, the geometric equation for the curve is 2-dimensional and it would be difficult to allow splitting and merging of contours using this formulation. The idea is to bypass this difficulty by geometrically embedding the formulation in 3 dimensions; i.e. considering the 2D curve as a slice of a 3D level curve and writing the dynamical equations for this 3D curve. The advantage is that topologically, the 3D curve remains connected when the 2D one gets disconnected.

The level set geometric snake, as first formulated by Caselles et al. [2], involves simple modifications of the geometrical equation which can be described as follows. The first modification is to describe the dynamical curve $C(\gamma,t)$ in term of the zero level set of a surface $\psi(x,y,t)$ evolving accordingly to

$$\frac{\partial \psi}{\partial t} = \left|\nabla \psi\right| \nabla \bullet \left(\frac{\nabla \psi}{\left|\nabla \psi\right|}\right)$$

Following Osher and Sethian [3], we note that the connection to the previous formulation is done bye (1) using the fact that $\{C(\gamma,t) \subset R^2 : \psi(C,t)=0\}$, (2) differentiating with respect to t and (3) using

$$\vec{N} = -\frac{\nabla \psi}{|\nabla \psi|} \qquad\qquad R = \nabla \bullet \left(\frac{\nabla \psi}{|\nabla \psi|} \right)$$

We then add to this equation an image dependent metric g(x,y) in order to allow snake evolution over a non-uniform background. A typical choice is

$$g(x,y) = \frac{1}{1 + |\nabla G \bullet I(x,y)|^n}$$

where G and I(x,y) have the same meaning as in Section 1 and n is a parameter that controls the sensitivity of the metric on the change of contrast in the image. In that form, g(x,y) = 0 near or on an edge and g(x,y) = 1 over a perfect uniformity. Adding g(x,y) to the relation for the zero level set makes the curve evolves in a manifold having a metric g(x,y). This means that if we want to minimize the perimeter of the curve, we need to minimize the length functional now given by

$$L_\varphi(t) = \int_0^1 \left| \frac{\partial C}{\partial \gamma} \right| g(\gamma) d\gamma$$

Minimizing and substituting variables, we get

$$\frac{\partial \psi}{\partial t} = g(x,y) \left[\nabla \bullet \left(\frac{\nabla \psi}{|\nabla \psi|} \right) + \nu \right] |\nabla \psi| + \nabla \psi \bullet \nabla g$$

where ν represents a constant advection term which causes a constant contraction/inflation of the front for positive/negative values, respectively. The effect of ∇g is to attract the evolving contour as it approaches an edge and to push the contour back out if it should pass the edge.

Using the formulation above, one of the main advantages of this method is that it allows the numerical implementation over a discrete grid in the (x,y) plane, which is not the case in the standard formulation (Section 1). However, still some problems remain if we try to discretize the set of equations naively by using a central difference scheme. As discussed in [3], one needs to respect an entropy criterion in order to ensure the continuity of the evolution. The solution to that problem has been discussed extensively in [3] and it requires to separate the level set evolution equation above in two parts:

$$\frac{\partial \psi}{\partial t} = F_0 + F(R)$$

where F_0 is the part not depending on the curvature and F(R) the part depending on it (these terms can be viewed as forces). Then the entropy criterion is satisfied if one approximates the constant advection term ν using upwind schemes, and the rest using standard central difference scheme (this is described in details in [4]). In addition, let us mention briefly that an apparent drawback of the formulation is that the numerical calculation of the front evolution requires updating $O(N^2)$ points for an (NxN) image. This can be substantially reduced by updating only points near the zero level set [4], which we have done in our implementation.

Finally, now that we have a dynamical principle, one needs to get initial conditions for the level set evolution. In our test, we mostly use a cone centered on a point (x_0,y_0) of the form:

$$\psi(x,y) = \sqrt{(x-x_0)^2 + (y-y_0)^2} - d$$

Where the zero level set is situated at distance d from the center (i.e. it is equal to zero). The level set is chosen to be negative in the interior of the snake and positive outside.

The total number of parameters necessary for a given segmentation is four, and each has a different meaning. Before we go on and provide examples, let us briefly describe these parameters:

- ν: this is the parameter appearing directly in the level set evolution equations. This is the advection term, when it is negative the snake will expand whereas when it is positive, it will shrink. The first case is useful when we want to segment contours from the interior of an image, examples will be provided below.
- σ: this parameter is hidden in the previous equations, it controls the smoothness of the gaussian (which is normalised). Typically we will have this parameter depends on the relation between the noise/object extent of the image. In the cases below, the noise fluctuations are around 1-2 pixels wide, so we will take a gaussian averaging over these pixel (i.e. $\sigma=3$ with gaussian coordinates given by the pixel positions).
- Δt: when the previous equations are discretized we need to set a scale of evolution, the value of this scale comes from experience (hidden here is the fact that we use unit spacial steps, i.e. $\Delta x=\Delta y=1$). If we allow it to be too big, then the snake will evolve in steps too large to be under control in the image and typically it will step over edges. When it is too small, the snake will take much more iterations to move significantly in the image.
- n: this parameter controls the metric g(x,y) described above. Typically is affects the dependence of the metric on the contrast in the image. The typical value is n=2 but, as we will describe below, for certain very low contrast cases, n=4 is also useful.

Although this seems to be a lot of adjustable parameters, their value remain very stable for identical types of images: the snakes developed here are very stable and we believe they could form a good base for automatic segmentation.

3. EXPERIMENTS ON A SYNTHETIC IMAGE

Before we go on and apply the technique on real radar images, let us concentrate on a synthetic image consisting of squares. The goal here is to show the influence of parameters on the segmentation. The original synthetic image as well as the noisy one are shown on Figure 1. Our goal is to segment the second largest square in the noisy image. For all cases below, we start with a snake barely encompassing the smallest square and let it expand.

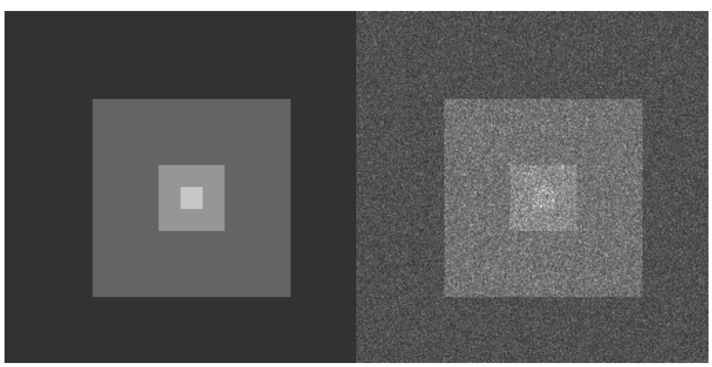


Figure 1: Synthetic an noisy images used in our experiments

The noisy image has been artificially degraded with a multiplicative log-normal noise of SNR=9.8 dB to simulate a speckle texture of radar images [5]. This noise level corresponds to an approximate number of looks of 3.4, which is typical of medium low resolution radar images. Here the amplitude of the noise is larger than the texture differences between the squares which make the resolution of edges by any standard method very difficult.

For results shown on Figure 2, we took $\Delta t=0.1$ and n=2. First, we note that the number of iterations increases with the advection's amplitude and decreases with σ. This is expected since the advection is a force term and the larger it is, the bigger is its effect. For σ , its value is an indication of the underlying metric smoothness and the larger it is, the larger is the gaussian on which we normalize the value of the intensity at one point. This makes for a smoother evolution and has the effect of reducing the noise in this image. For $\sigma=1$, we observe that the snake is trying to segment every little noisy point giving us a bad segmentation. It cannot distinguish between the local edges (created by the noise) and the macroscopic ones. As σ increases, the local noisy points are averaged over and, apart from certain sections where random noisy points “conspired” to have similar intensity, we see that the snake is segmenting the square well. We still have some wiggles but this is expected given the intensity of the noise which is well beyond the macroscopic changes in intensity between the squares. For σ=3, we get a fair segmentation.

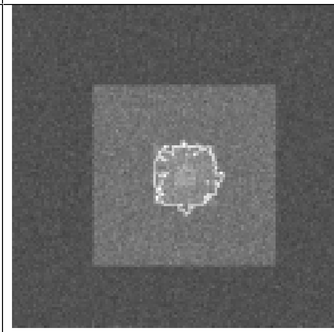
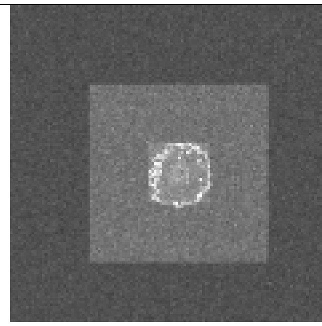
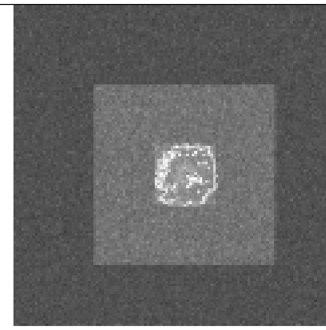
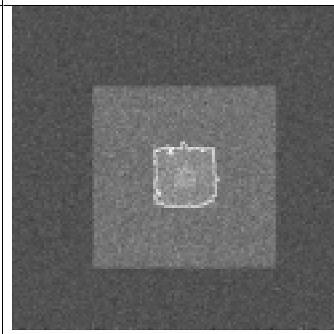
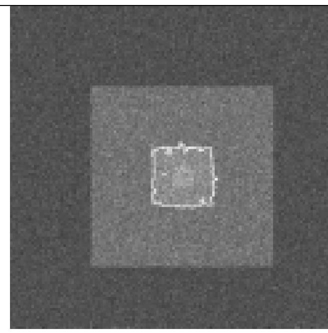
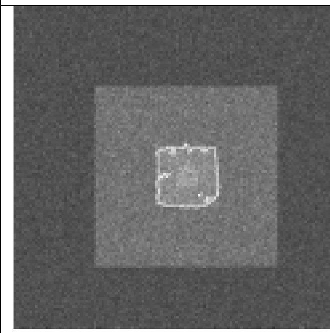
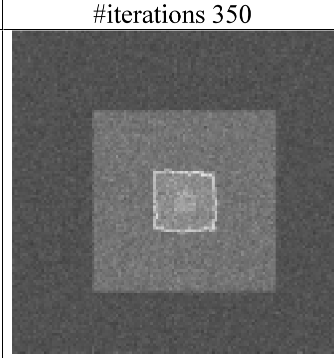
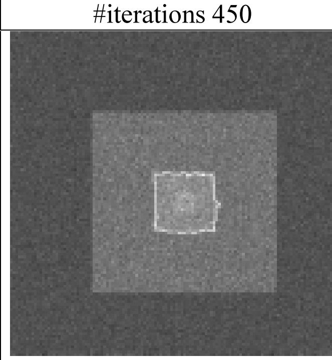
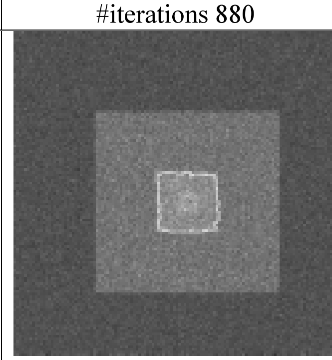
	ν=–4.0	ν=–3.0	ν=–2.0
σ=1.0	 #iterations: 500	 #iterations 700	 #iterations 1400
σ=2.0	 #iterations 350	 #iterations 450	 #iterations 880
σ=3.0	 #iterations 310	 #iterations 350	 #iterations 680

Figure 2: Various snake behaviors for the artificially degraded synthetic image on Figure 1

4. APPLICATION TO RADAR IMAGES

In this section we present our results regarding contour segmentation on real radar images using the level set-based snakes method described in Section 2.

1. Coastline detection

The first example (Figure 3) is an Airborne SAR image of the Antigonish region between eastern part of Nova-Scotia (Canada) and Cape-Breton Island (bottom part of Figure 3) [6]. The image has been acquired in C-band using a HH polarisation at a resolution of 15.6 m/pix. The image size is 1122 x 434 pixels. The goal here is to extract the coastline. In order to illustrate the topological merging of snakes, we started this segmentation with four very small snakes in inflation. Figure 3 shows the initial configuration, while Figure 4 and Figure 5 give the intermediate and final states, respectively.

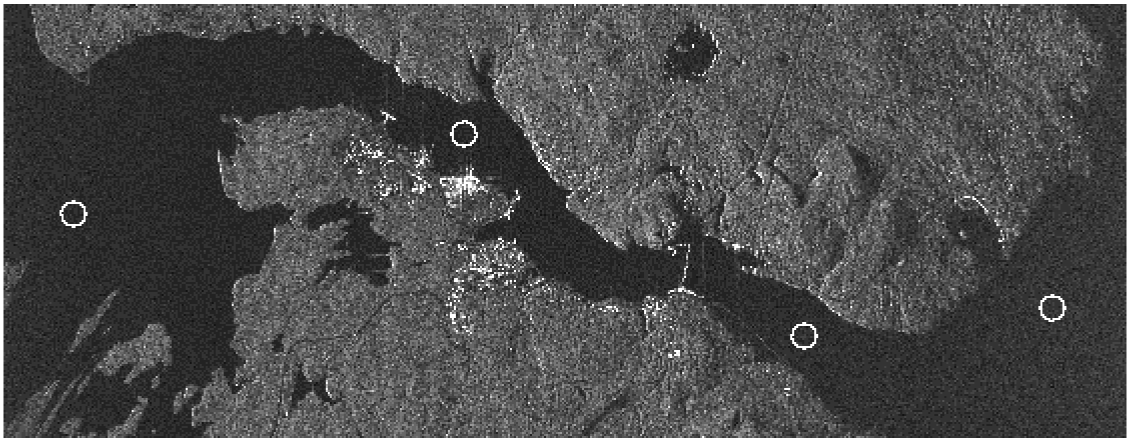


Figure 3: Initial configuration for an experiment of coastline detection

The snake parameters were chosen to be $\nu=-4.0$, $\sigma=3.0$, $\Delta t=0.1$ and $n=4$. The first three parameters are standard, the negative ν forcing an inflating snake. We must discuss a little the choice of n=4 which defines the behavior of the metric. As said above, one usually takes n=1 or 2 [2,4]. This parameter controls the sensitivity of the metric on the change of contrast in the image. Here we are faced with an image for which the background is very dark and uniform with coastlines being sharp at some places, noticeably in the center of the image, but being very blur on the right hand side for example. If we had chosen n=1 or 2, then the snake would have seen the change of contrast as being minimal and it would have gone, for example, through the coast on the right hand side. With n=4, we get the result shown on Figure 4 after 300 iterations.

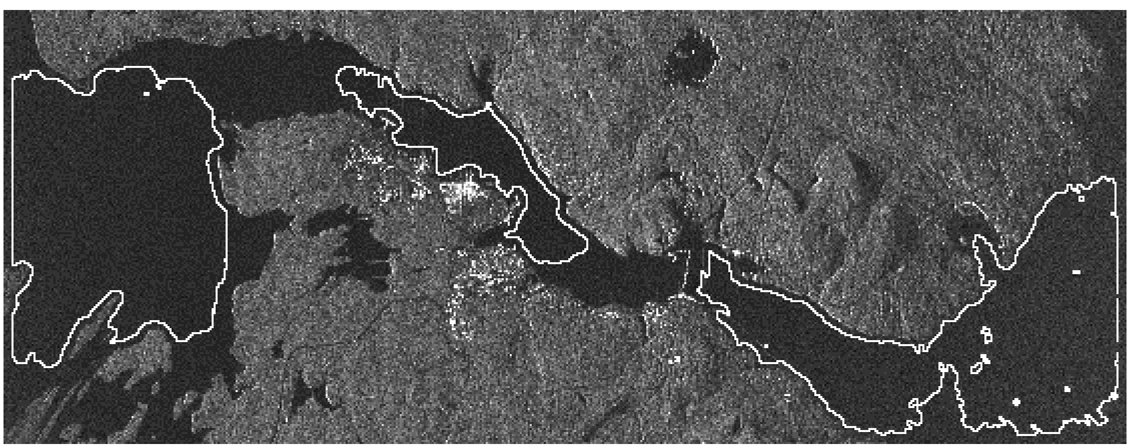


Figure 4: Snake evolution after 300 iterations

We observe that the two right-hand side snakes have merged (there are still local fluctuations, but they will disappear in the forthcoming iterations) whilst the ones on the left are still separated.

After 1100 iterations, we get the fully segmented image shown on Figure 5. Here we observe that the coast line has been properly segmented by the snake. At the lower left side, there are still a few islands that are not properly done but this is due to the fact that at that resolution, the snake could not squeeze between the islands. This can encompassed by either using a higher resolution or adding another snake in the region.

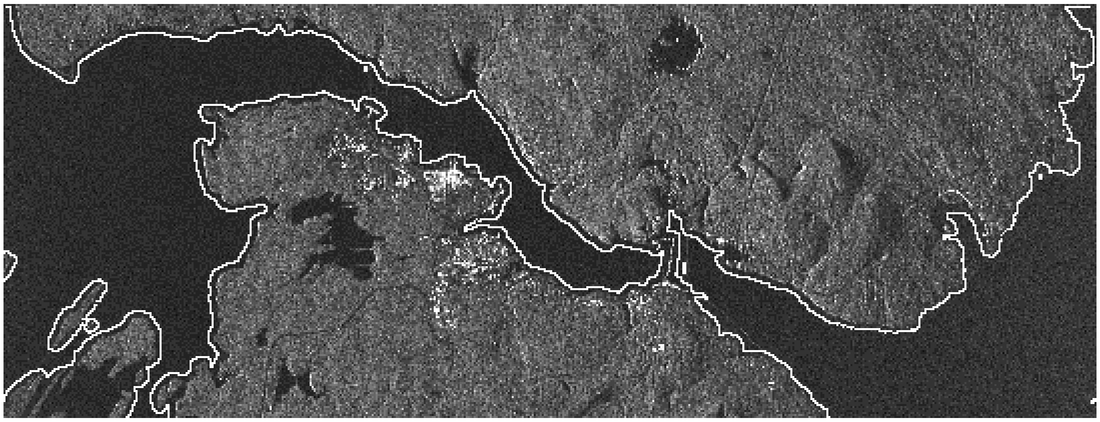


Figure 5: Snake evolution after 1100 iterations

2. Flooded area detection

Figure 6 shows a Radarsat-I image of a portion of the Winnipeg area during the Red River flood in 1997 [7]. The image shows water (black areas) over fields. The image has been acquired in standard mode at a resolution of 12.5 m/pix. The image size is 900 x 701 pixels. The goal here is to find the limits of the flooded areas, which in this image are the black are as. In addition to speckle noise, there is a lot of interference objects (in particular roads) for contour extraction of flooded areas in the image. We start the process using three initial circular snakes as shown in Figure 6. As we see, the regions limits are highly non-trivial and our starting snakes are far from the segmented image.

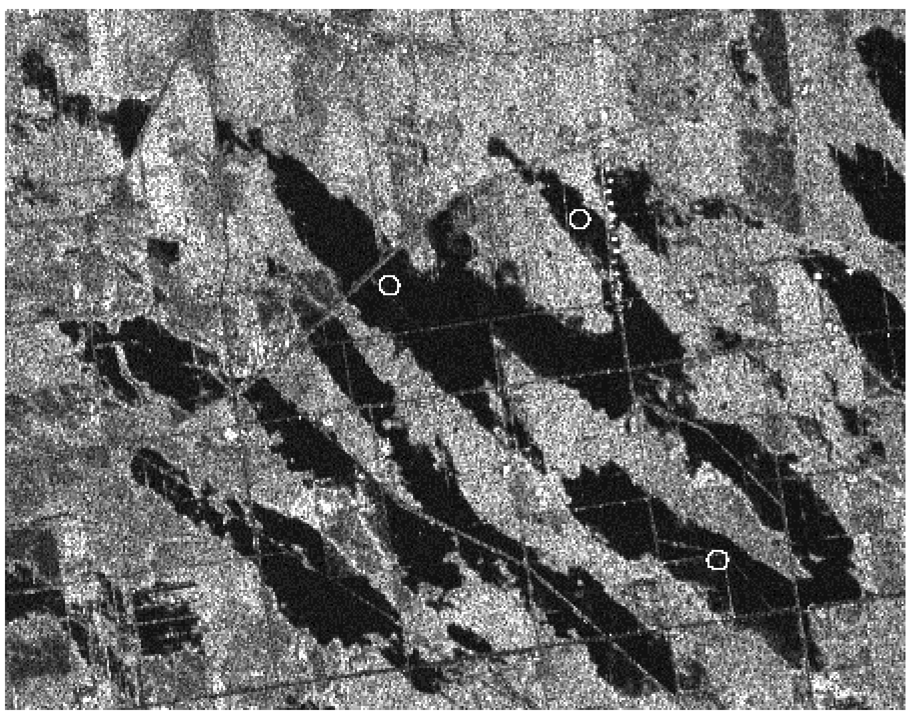


Figure 6: Initial configuration for an experiment of flooded areas detection

The parameters values were again chosen as $\nu=-4.0$, $\sigma=3.0$, $\Delta t=0.1$ and $n=4$. But here, because of the noisy environment, the snake will need more iterations to evolve. After 4400 iterations we get the image shown on Figure 7. We observe a fair segmentation which allows us to discuss the advantages and flaws of the approach. For this application, a clear advantage is that the evolution of the snake is local, i.e. we can concentrate finding edge in a specific region. Another advantage for the flooding image is that it is very easy from this approach to get the area of the flooding just segmented: the level set is negative inside the snake so that we only need to count the number of negative points. This is peculiarly useful here where we see some very small areas having islands of dry land. For non-trivial (and maybe non-closed) topologies, this could take significant computing time. A drawback though is well identified from Figure 7: the snake has difficulty to get to thin regions, typically this problem would be settled again by increasing the resolution.

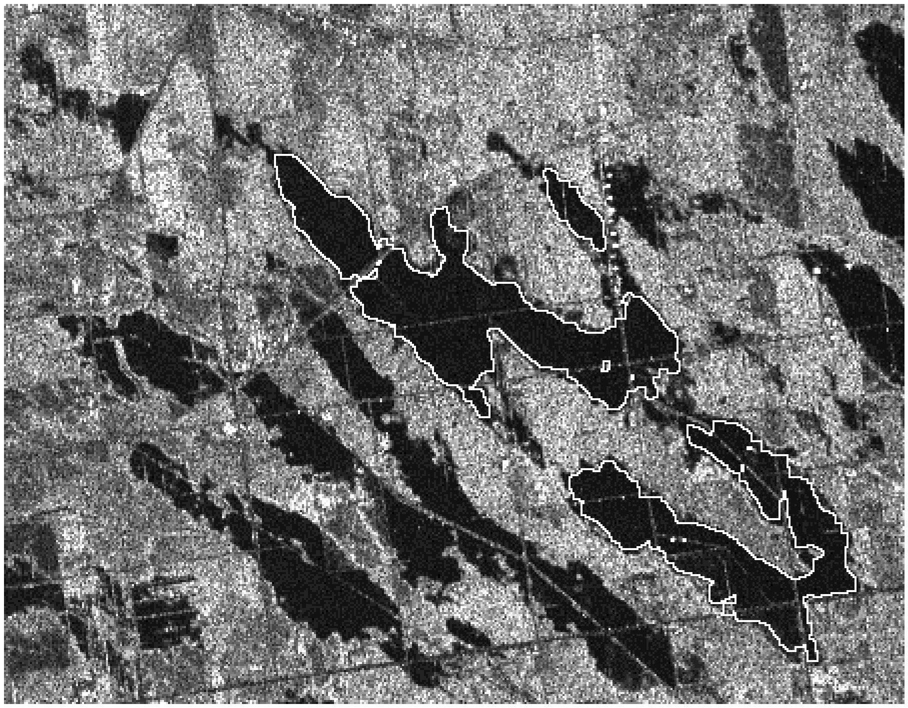


Figure 7: Snake evolution after 4400 iterations

3. Target segmentation

We have also tested the level set-based snakes approach for the segmentation of ship targets in ISAR images. Traditionally, the approach is to go through a chain of processes to segment such an image [8]. This is required because of the noise in ISAR images and also because such images does not have a uniform contrast along the contour. Snakes simplify the segmentation process. We present in Figure 8 the segmentation of two ISAR images (image size is 256 x 92 pixels) of a same ship (the two images are taken at different times) with parameters $\nu=-4.0$, $\sigma=3.0$, $\Delta t=0.1$ and $n=2$, after 500 iterations. The initial snake is a circle surrounding the ship.

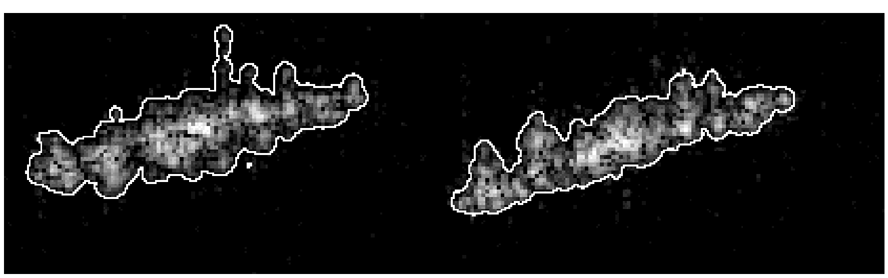


Figure 8: Final snake configuration for two examples of target segmentation in ISAR images

On the left-hand side of Figure 8, we see that the snake correctly segments the funnel which is very faint. On the right-hand side, there is no funnel because of a different ship rotation with respect to its center of mass, during image acquisition. For other snake parameters, it is even possible to separate the important scatterers along the ship deck (Figure 9). In that case, the segmentation could serve as a processing step for a ship classifier based on the position of these strong scatterers.

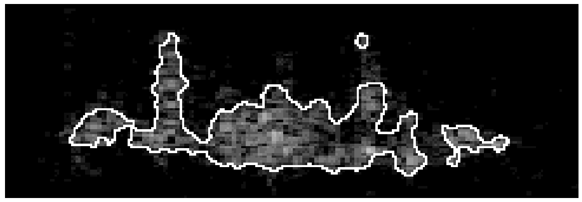


Figure 9: Final snake configuration for an experiment of target segmentation in ISAR images

5. CONCLUSION

In this paper, we have demonstrated the applicability of level set-based snakes, for contour segmentation in radar images. Level set-based snakes, have important advantages over the standard approach:

- initial snake position can be very far from the final state
- snakes can merge and split
- various parameters make level set-based snakes more flexible to various image types
- they are more robust to noise

Last point is a very important one for coherent imaging like radar. Edge detection is always a difficult problem in SAR images which usually require extensive image pre- or post-processing. Our experiments show that level set-based snakes seem to be a viable alternative to edge detection techniques in SAR images, especially for semi-automatic water-terrain separation. In addition, when implemented correctly, the computational complexity is quite slow as it is proportional to the snake length, not the image size (snake presented above took not more than one minute of CPU time to calculate on a 300 MHz Pentium).

Our experiments show that level set-based snakes are of enough practical interest to deserve further work, especially regarding the automatic aspects of the implementation. For instance, a procedure to find initial "point" snakes (seed points) over a water area in SAR images could be coupled to the current algorithm in order to provide an automatic coastline detection tool. Other extensions to the present work concern the applicability to other image modalities.

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