This paper presents a novel geodesic active contour (GAC) model based on an edge detector for rapid detection of water bodies from spaceborne synthetic aperture radar (SAR) imagery with high speckle noise. The original edge indicator function based on gradients is replaced by an edge indicator function based on the ratio of exponentially weighted averages (ROEWA) operator. Thus, the capability of edge detection and the accuracy of locating edges are greatly improved, which makes the model more appropriate for SAR images. In addition, an enhancing term is added to the original model’s energy function in order to boost the strength for the contour’s evolution. An unconditionally stable additive operator splitting (AOS) scheme and a fast algorithm for re-initialization of the level set function are adopted, which not only enhances the model’s stability, but also speeds up the model’s convergence remarkably. The experimental results on simulated and real RADARSAT-1/-2 images show its efficiency and accuracy.

1. Introduction

Water resources play an important role in environmental, transportation and regional planning, disaster management, industrial and agricultural production. Detecting water bodies is the first step for any planning, especially for Ontario, Canada, where the land-cover is dominated by water bodies. Earth observation data, including spaceborne synthetic aperture radar (SAR) images, when used jointly with in situ data, can provide an essential contribution for the creation of inventories of surface water resources, the extraction of thematic maps relevant for hydrogeographical studies and models (e.g., land cover, surface geomorphology) or for the retrieval of (bio)geographical parameters (e.g., water quality and temperature, soil moisture) [Shultz and Engman 2000]. SAR data are suitable for mapping water bodies, as the signal is principally sensitive to moisture and to surface roughness. These data can be preferred to optical imagery taking into consideration the cloud penetration capabilities that are fundamental when mapping transient waters typically associated to rainy periods. However, speckle noise usually occurs in SAR images due to the nature of coherent imaging. It makes feature extraction from SAR image much more difficult than that from optical imagery. In order to eliminate the speckle effects, a significant research effort has been devoted to the design of effective segmentation methods over last few decades. Among them, four types of the segmentation methods have been commonly used, namely, the edge-based scheme [Oliver et al. 1996; Collins and Kopp 2008], the Markov random field (MRF) model [Fjortoft et al. 2003], level set theory [Shu et al. 2010], and the region merging / region growing family of methods [Cook et al. 1994]. The edge-based scheme aims to find transitions between uniform areas, rather than directly identifying them.
The algorithms based on this technique generally use an edge detection operator. However, it has been shown that these edge-based detectors introduce a bias and increase the variance in the estimation of the edge position when the window does not have the same orientation as the edge [He 2009]. The MRF model presents many interesting properties since it allows designing segmentation techniques by taking into account the nature of the fluctuations in a statically optimal way. However, the MRF model introduces several parameters which cannot be easily determined automatically, and may lead to a difficult optimization problem. The narrow band level set segmentation method presented by Shu et al. [2010] uses thresholding combined with morphological filtering to segment SAR imagery into land and water followed by refining the segmentation results using level set theory. The region merging methods, such as the merge using moments (MUM) method [Cook et al. 1994], use the statistical properties of adjoining regions to merge similar regions. Although these methods usually produce acceptable segmentation results for large textured areas they do not perform well for small targets. Besides, the choice of the parameters can affect the final segmentation.

In recent years, segmentation methods based on active contours have gained tremendous popularity [Kass et al. 1988; Cohen 1991; Sethian 1996; Zhu and Yuille 1996; Caselles et al. 1997; Osher and Sethian 1998]. Active contours were initially introduced in the form of snakes by Kass et al. [1998]. The method aims at segmenting an image by deforming an initial contour towards the edge of the object of interest. This is done by deforming an initial contour in such a way that it minimizes an energy functional defined on contours. Despite its success, the original parametric active contour model has two noticeable drawbacks. First, it depends on the parameterization of the evolving contour and thus is not geometrically intrinsic. Second, it cannot naturally handle changes in the topology of the evolving contour. These drawbacks were addressed by the geodesic active contour (GAC) model [Caselles et al. 1997]. In this model, the energy functional is minimized as a geodesic computation in a Riemann space. Also, the evolving contours are embedded in a higher-dimensional level set function [Osher and Sethian 1998]. This model can easily handle segmentation of several objects, since its level set implicit surface representation remains continuous even if the contours split. However, wrong segmentation results may be produced when the model is applied to SAR imagery. The reason may be that the GAC model exploits a gradient operator to detect edges and the edge map based on gradients is disordered in SAR imagery. Classical differential edge detectors are not well adapted to SAR imagery since their false alarm rate depends on the mean reflectivity: they usually detect more false edges in the areas of high reflectivity than that of low reflectivity [Touzi et al. 1988; Germain and Refregier 2001]. Hence, edge detectors specifically for SAR images have been developed. The common property of these detectors is that they compute the ratio of averages instead of the difference. Bovik [1988] and Touzi et al [1988] defined filters which compute the normalized ratio of averages (ROA). Fjortoft et al. [1998] derived a filter from a stochastic image model, whose expression is a modified version of Shen and Castan [1992] - the ratio of exponentially weighted averages is considered. In the framework of statistical decision theory, Oliver et al. [1996] determined an optimal filter, based on the likelihood ratio (LR) principle. The ROA and LR operators use the arithmetic mean for the estimation of local mean values, which are optimal only in the mono-edge case, whereas the ratio of exponentially weighted averages (ROEWA) operator is optimal under a stochastic multi-edge model and more appropriate for SAR images. Recently, several researchers [Chesnaud et al. 1998, 1999; Germain and Refregier 2001; Martin et al. 2004] have developed several active contour methods for edge detection or segmentation of SAR imagery. Their results are promising, but the active contour model they used is parametric. As shown above, it is sensitive to the initial condition and cannot naturally handle changes in the topology of the evolving contour.

In this paper, we propose a novel GAC model based on the ROEWA operator [Fjortoft et al.1998] under the criterion of energy minimization. The idea is that the original edge indicator function based on gradients is replaced by a new edge indicator function based on the ROEWA operator. Thus, the capability of detecting edges and the accuracy of locating edges are greatly improved, which makes the model more appropriate for SAR image segmentation. In addition, a “balloon force” term is added to the energy functional of the original model in order to boost the strength for the contour’s evolution. As a result, the contour’s evolution takes less time and the sensitivity to the initial contour is reduced. In the numerical implementation of the model, an unconditionally stable additive operator splitting (AOS) scheme [Weickert et al. 1998] and a fast algorithm for re-initialization of the level set function [Fleischman and Huttenlocher 2004] are adopted, which not only improve the model’s stability, but also speed up the model’s convergence remarkably. The proposed model shows good performance in dealing with two-
class segmentation of SAR images. The remainder of the paper is organized as follows. Section 2 briefly reviews the background of the GAC model and explains its unsuitability in SAR image segmentation. Section 3 describes the ROEWA operator and the associated GAC model. Section 4 discusses the numerical implementation scheme and the related segmentation algorithm based on the proposed model. Section 5 presents experimental results on both simulated and real RADARSAT-1/2SAR images. The performance evaluation is described in Section 6. Finally, Section 7 concludes the study.

2. Background

Let \( x \) be the abscissa, \( y \) be the ordinate, \( \Omega \subset \mathbb{R}^2 \) be the image domain, \( u_0(x, y) : \Omega \to \mathbb{R}^+ \) be a given image, \( C \) be a planar contour with the length \( L(C) \) and \( C(s) = (x(s), y(s)) : [0, L(C)] \to \mathbb{R}^2 \) be its arc-length parameterization, where \( s \) denotes an arclength variable. The classical GAC model associates the contour \( C \) with an energy given by [Caselles et al. 1997]

\[
\int_0^{L(C)} g(|\nabla u_0(C(s))|) ds
\]

where \( \nabla u_0(C(s)) \) is the image gradient defined on the contour, \( |\nabla u_0(C(s))| \) denotes the magnitude (modulus) of the gradient. The edge indicator function \( g(r) : [0, \infty) \to \mathbb{R}^+ \) is a strictly decreasing function, such that \( g(0) = 1 \) and \( g(r) \to 0 \) as, \( r \to \infty \) where \( r \) denotes an arbitrary variable. According to the calculus of variations and the gradient descent method, we can obtain the evolution equation for the contour \( C \) [Caselles et al. 1997]

\[
\frac{\partial C}{\partial t} = \left[ g\kappa - \langle \nabla g, \nabla \rangle \right] n
\]

where \( \kappa \) is the mean curvature, \( n \) is the unit inward normal. Eq. (2) is well-defined because an associated unique viscosity solution exists [Caselles et al. 1997]. Osher and Sethian [1998] introduced the level set method to implicitly solve the contour propagation problem and to deal with topological changes. In the level set framework, the evolving contour \( C \) is defined implicitly as the zero level set of an embedding scalar function \( \phi \), such that \( C(t) = \{(x, y) : \phi(x, y, t) = 0\} \), where \( t \) denotes a time variable. By convention, we assign negative values to the interior and positive values to the exterior of the contour. According to the level set method, Eq. (2) can be written in the level set form as follows [Caselles et al. 1997]

\[
\frac{\partial \phi}{\partial t} = g\kappa \left| \nabla \phi \right| + \nabla g \cdot \nabla \phi
\]

3. Proposed Model

3.1 ROEWA Operator

The ROEWA operator, proposed by Fjortoft et al. [1998], is based on a linear minimum mean square error (MMSE) filter. In the one-dimensional (1D) case, the linear MMSE filter can be expressed as

\[
f(x) = C \exp \{-px|\}
\]

where \( C \) is the normalizing constant, \( p \) is the filtering coefficient. In the discrete case, \( f(x) \) can be implemented very efficiently by a causal filter \( f_1(x) \) and an anticausal filter \( f_2(x) \)

\[
f(x) = \frac{1}{1 + b} f_1(x) + \frac{1}{1 + b} f_2(x-1), x = 1, 2, \ldots, N
\]

where \( f_1(x) = e^{-ax} H(x), f_2(x) = e^{-ax} H(-x), 0 < b = e^{-a} < 1, a = 1 - b \), \( H(x) \) is the discrete Heaviside function. If \( x \geq 0 \) equals to one, otherwise zero.

Based on the linear MMSE filter, the ROEWA operator can be defined as

\[
\begin{align*}
\rho_{X_{\max}}(x, y) &= \max \left\{ \beta_{X_1}(x - 1, y), \beta_{X_2}(x + 1, y) \right\} \\
\rho_{Y_{\max}}(x, y) &= \max \left\{ \beta_{Y_1}(x, y - 1), \beta_{Y_2}(x, y + 1) \right\}
\end{align*}
\]

where \( \beta_{X_1}, \beta_{X_2}, \beta_{Y_1}, \) and \( \beta_{Y_2} \) are the exponentially weighted averages, which can be obtained by

\[
\begin{align*}
\beta_{X_1}(x, y) &= f_1(x) * \{ f(y) \cdot u_0(x, y) \} \\
\beta_{X_2}(x, y) &= f_2(x) * \{ f(y) \cdot u_0(x, y) \} \\
\beta_{Y_1}(x, y) &= f_1(y) * \{ f(x) \cdot u_0(x, y) \} \\
\beta_{Y_2}(x, y) &= f_2(y) * \{ f(x) \cdot u_0(x, y) \}
\end{align*}
\]

where \( \ast \) denotes the convolution in the horizontal direction and \( \cdot \) denotes the convolution in the vertical direction. With analogy to gradient-based edge detectors, the magnitude of the ROEWA operator can be defined as

\[
r_{\text{max}}(x, y) = \sqrt{r_{X_{\max}}(x, y)^2 + r_{Y_{\max}}(x, y)^2}
\]

Figure 1 shows water boundaries extracted from a RADARSAT-1 image using the ROEWA operator. The edges found by the ROEWA operator appear to be consistent with actual edges on the whole. Consequently, the ROEWA operator may be appropriate for detecting edges in SAR imagery.
3.2 GAC Model Based on the ROEWA Operator

Based on the ROEWA operator, the new energy functional of the GAC model can be defined as

\[
\int_0^{L(C)} g(|r_{\text{max}}|) ds + \alpha \int_\omega g(|r_{\text{max}}|) da
\]

(9)

where \( g \) is the edge indicator function based on the magnitude of the ROEWA operator, which stops the contour in the vicinity of edges

\[
g(|r_{\text{max}}|) = \frac{1}{1 + \frac{|r_{\text{max}}|^2}{\lambda^2}}
\]

(10)

where \( \lambda \) is a scaling constant. \( g \) is bounded to [0, 1], and the more it approaches zero, the better it closes to the edge. In the above functional, the second term is a “balloon force” term to enhance the power for the contour’s evolution. As a result, the speed of the contour’s evolution is increased and the sensitivity to the initial contour is reduced. \( a \) is a constant that aims to keep the contour moving in the proper direction. If \( a > 0 \), the contour deflates; otherwise inflates. \( da \) is the area element and \( \omega \) is the region inside the contour \( C \).

The calculus of variations and the gradient descent method provides the following evolution equation for the contour \( C \)

\[
\frac{\partial C}{\partial t} = [g\kappa + ag - (\nabla g \cdot \nabla)]A
\]

(11)

According to the level set method, the evolution equation with respect to the level set function \( \phi \) is

\[
\frac{\partial \phi}{\partial t} = g(\kappa + a) \nabla \cdot \nabla \phi + g \nabla \cdot \nabla \phi
\]

(12)

where \( \kappa = \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \). To facilitate the numerical calculation, we rewrite Eq. (12) as follows in terms of the property of the divergence

\[
\frac{\partial \phi}{\partial t} = \phi \text{div} (\tilde{A}) + \tilde{A} \cdot \nabla \phi
\]

\[
\frac{\partial \phi}{\partial t} = \text{div} \left( g \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \right) + \alpha g \nabla \phi
\]

(13)

4. Implementation

It is very difficult to directly solve Eq. (13). A numerical scheme is usually adopted to obtain an approximated solution. The first term \( \text{div} \left( g \frac{\nabla \phi}{|\nabla \phi|} \right) \) in Eq. (13) is a parabolic term. Although this regularizing term is indispensable for the correct evolution, it makes the resulting partial differential equation particularly stiff, numerically. If we use a simple explicit method for numerically evolving the contour, then instability incurs unless very small time steps are applied (\( \tau < h^2 / 4 \), where \( \tau \) is the time step, \( h \) is the space step). To overcome this shortcoming, we could use an implicit scheme, which is unconditionally stable and thereby free of the time step limitation. However, a system of equations needs to be solved at each time step, which is complex and time-consuming. On the other hand, the AOS scheme is not only stable but also easy to implement. Therefore, we use this scheme to solve the evolution equation numerically.

4.1 Numerical Scheme

The AOS scheme was introduced by Weickert et al. [1998] as an unconditionally stable numerical scheme for the nonlinear diffusion equation in the form of \( \frac{\partial u_0}{\partial t} = \text{div} \left( g(\nabla u_0) \nabla u_0 \right) \). Comparing it with Eq. (13), we find that there are differences
between these two equations and thus their results cannot be directly compared. In fact, if we define the level set function $\phi$ as a signed distance function (using the Euclidean distance)

$$
\phi(x, y) = \begin{cases} 
-\sqrt{(x-x_0)^2 + (y-y_0)^2}, & \text{if } (x, y) \text{ is inside } C \\
0, & \text{if } (x, y) \text{ is on } C \\
\sqrt{(x-x_0)^2 + (y-y_0)^2}, & \text{if } (x, y) \text{ is outside } C 
\end{cases}
$$

(14)

where $(x_0, y_0)$ is the point on the contour $C$ (embedded in the zero level set of $\phi$) with the minimum distance from the point $(x, y)$, we obtain $|\nabla \phi| = 1$. Consequently, Eq. (13) becomes

$$
\frac{\partial \phi}{\partial t} = \text{div}(g \nabla \phi) + \alpha g
$$

(15)

Eq. (15) can be solved numerically by the AOS scheme in Weickert et al. [1998].

By defining two matrix operators: $A_1 = \frac{\partial}{\partial x}(g \frac{\partial}{\partial x})$, $A_2 = \frac{\partial}{\partial y}(g \frac{\partial}{\partial y})$, we can rewrite Eq. (15) as

$$
\frac{\partial \phi}{\partial t} = (A_1 + A_2)\phi + \alpha g
$$

(16)

Because the edge indicator function $g$ is defined on the magnitude of the ROEWA operator and thereby it is independent of the level set function, the operators $A_1$ and $A_2$ keep fixed during the whole evolution process. It is favorable for the numerical calculation of the GAC model.

Let $\tau$ be the time step, $h$ be the space step, and $(x_i, y_j) = (ih, jh)$ be the grid points, for $1 \leq i \leq N_x$, $1 \leq j \leq N_y$, ($N_x$ and $N_y$ are the pixel numbers in the horizontal and vertical direction, respectively).

Furthermore, let $\phi^n_{i,j} = \phi(n\tau, x_i, y_j)$ be an approximation of $\phi(t, x, y)$. The level set function $\phi$ at the time $n\tau$ is discretized as a matrix $[\phi^n_{i,j}]_{N_x \times N_y}$. On the other hand, variables in the AOS scheme are represented in the form of column vectors. Hence, the matrix $[\phi^n_{i,j}]_{N_x \times N_y}$ should be converted to a column vector. If we scan the pixels lexicographically in a row-major order and concatenate the results in each row, we obtain a column vector $\phi$ with the size $N = N_x \times N_y$. The edge indicator function $g$ can be also changed to the corresponding vector. Based on the above results, the AOS scheme for Eq. (16) is achieved [Weickert et al. 1998; Goldenberg et al. 2001]

$$
\phi^{n+1} = \frac{1}{2} \sum_{l=1}^{\sum_{j=1}^{N_y}} \left[ I - 2\tau A_l \right]^{-1} \left( \phi^n + \tau \alpha g \right)
$$

(17)

The discrete expression of the matrix operators $A_l$ $(l = 1, 2)$ should be provided in order to fulfill the calculation of Eq. (17). Assume that $A_l = [a_{ij}]_{N_x \times N_y}$ then each element of this matrix is assigned by:

$$
a_{ij} = \begin{cases} 
g_i + g_j, & j \in N(i) \\
-\sum_{k \in N(i)} g_i + g_j, & j = i \\
0, & \text{else}
\end{cases}
$$

(18)

where $N(i)$ is the set of two neighbors of the pixel $i$ (boundary pixels have only one neighbor) in the horizontal or vertical direction. Although the expression forms of $a_{1,ij}$ and $a_{2,ij}$ are identical, the actual values are totally different. In fact, $N(i)$ refers to two horizontal neighboring pixels for, $a_{1,ij}$ i.e., $i - 1$ and $i + 1$; whereas for, $a_{2,ij}$, $N(i)$ is two vertical neighboring pixels, i.e., $i - N_x$ and $i + N_x$.

According to the formulation of $A_l$ $(l = 1, 2)$, one can see that the matrix $I - 2\tau A_l$ is tridiagonal and diagonally dominant and therefore can be efficiently solved by the so-called Thomas algorithm [Weickert et al. 1998].

4.2 Re-initialization of the Level Set Function

As mentioned above, it is necessary to keep the level set function $\phi$ as a signed distance function such that $|\nabla \phi| = 1$ before applying the AOS scheme. However, the level set function will deviate from the signed distance function during the evolution. To avoid this problem, $\phi$ should be re-initialized to a signed distance function before each iteration. There are several distance transform algorithms for the level set re-initialization. One of the most common approaches is the fast marching (FM) algorithm proposed by Sethian [1996]. The FM algorithm utilizes an efficient insert-sort procedure based on heaps and has the complexity of $O(N \log N)$, where $N$ is the pixel number. Recently, a new distance transform algorithm was proposed by Felzenszwalb and Huttenlocher [2004] and used by Papandreou and Maragos [2007]. It can rapidly re-initialize $\phi$ to a distance function with the complexity of $O(N)$. Furthermore, their algorithm is very easy to implement. Hence, we use it as the re-initialization tool. The basic idea of this algorithm is as follows.

Let $\Omega = \{1 \ldots N_x\}$ be a 1D grid, and $f: \Omega \rightarrow R$ an arbitrary function on the grid. The squared Euclidean 1D distance transform of $f$ is given by
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difference equation. Usually, \( h = 1 \). In Eq. (17), \( \tau \) is the time step for the difference equation. We mention that the choice of the time step is a compromise between the accuracy and the efficiency. Choosing larger step can speed up the evolution, but may also cause errors in the edge location. Usually, the time step \( \tau \) should be less than 10.0.

5. Results and Discussion

Two simulated and two real RADASAT-2 SAR images were used to validate the segmentation algorithm. The experiments were carried out with MATLAB V7.4 on a PC with a Pentium IV 1.8 GHz CPU and 1 GB RAM. The kernel code for the AOS scheme was implemented in C++. The parameters used in the experiments are as follows: \( b = 0.7, a = 1 - b = 0.3, \lambda = 0.1, h = 1, \tau = 5 \) and the “balloon force” parameter \( a \) is adjusted according to the specific image.

The algorithm was first applied to two simulated images. The purpose of this experiment was to evaluate its capability of detecting edges and to assess the accuracy of locating edges. The simulated images were obtained by multiplying an optical image by a white exponential speckle noise. The equivalent number of independent looks (ENIL) of these images is 1. The dimensions of the images are 256 × 256 and 107 × 100 pixels, respectively. The reflectivity contrast of the two simulated images is 41.5497 and 7.204 respectively. The initial contour was represented by a rectangle close to the image boundary. The parameter \( a \) was set to 0.68 for both images. The algorithm took about 7.4 seconds and 3.7 seconds to produce the results. As shown in Figure 3, the object edges are accurately located and the circle regions are correctly segmented. Consequently, the results demonstrate desirable performance of the algorithm in the presence of the image with multiplicative noise.

Two RADARSAT-1 and five RADARSAT-2 images were used in this study. The ENIL of these images is 1. The sizes of RADARSAT-1 image extracts are 475 × 350 and 615 × 310 pixels, respectively and the dimensions of all RADARSAT-2 images are 435 × 342 pixels. The equivalent look number of all the image extracts is 1. The reflectivity contrast of the following RADARSAT-1 and -2 images are 62.0686, 27.0-422, 19.8717, 23.3076, 14.4959, 21.5752 and 16.346, respectively. The initial contour was set to a rectangle very close to the image boundary. The parameter \( a \) was set to 0.85, 0.80, 0.85, 0.80, 0.83, 0.90 and 0.90, respectively. The execution time for RADARSAT-1 image processing was about 13.9 seconds and 20.6 seconds and for RADARSAT-2 image processing was about 12 seconds, respectively. Figures 4 and 5 show the corresponding segmentation results, in which the water regions are correctly segmented. The experimental results demonstrate that the algorithm performs well for real SAR images. Furthermore, the computational cost is relatively low, so the algorithm is a practical candidate for SAR image segmentation. In addition, the settings for the initial contour are almost identical for all images, which indicate that the algorithm is not sensitive to the initial conditions as is the classical Snakes algorithm.

Figure 3: Segmentation results of two simulated SAR images using our method. (a) Two original optical images. (b) Simulated SAR images with initial contours; (c) Detected contours; (d) Segmentation results.
6. Performance Evaluation

6.1 Quality Evaluation

Objective assessment of an algorithm’s performance requires testing the consistency between the segmentations it produces and the cartoon model upon which it is based. The cartoon model is an image model where a real image with detailed contents is represented by a large scale piecewise smooth image with several gray levels. This means that segments must be homogeneous and statistically distinct from their neighbors. The latter condition can be forced by segment merging, so that segments need only be tested for homogeneity.

Here we adopt two methods from Caves et al. [1998] to carry out such tests for an arbitrary segmentation. Caves et al. [1998] defined two quality criteria for real images: intensity variance of the ratio intensity ratio image $D$. Suppose the original image $u_0$, the segmented image $u_{seg}$, and the size of image is $m \times n$, then the ratio image $RI$ is defined as follows:

$$RI = u_{seg} / u_0$$

The ratio image shows the residual structure of the original image after the region segmentation, which can be used to measure the performance of segmentation. Based on the ratio image, two quality criteria can be defined as follows:

$$\sigma_{RI}^2 = \frac{1}{L} \sum_{k=1}^{L} \frac{n_k}{mn} \left( \frac{RI_k - \overline{RI}}{\overline{RI}} \right)^2$$

$$D = \frac{1}{L} \sum_{k=1}^{L} \frac{n_k}{mn} \ln(\overline{RI_k})$$

where $L$ is the sub-region numbers of the ratio image, $RI_k$ is the $k$-th sub-region of the ratio image, $n_k$ is the pixel numbers of $RI_k$, $\overline{RI_k}$ and $\overline{RI}^2_k$ are the mean of square and square of mean of $RI_k$ separately. The two parameters are zero only when all pixels have the same intensity. Therefore the segmented region is homogeneous when these two parameters approach zero. The evaluation results of segmentation quality for real images are shown in Table 1.

<table>
<thead>
<tr>
<th>Size (pixel)</th>
<th>64 × 64</th>
<th>128 × 128</th>
<th>256 × 256</th>
<th>512 × 512</th>
<th>1024 × 1024</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time (sec.)</td>
<td>1.7</td>
<td>6.1</td>
<td>26.5</td>
<td>143.6</td>
<td>864.8</td>
</tr>
</tbody>
</table>

Table 1: Evaluation results of segmentation quality for two RADARSAT-1 and five RADARSAT-2 images.

<table>
<thead>
<tr>
<th>RADARSAT-1</th>
<th>RADARSAT-1</th>
<th>RADARSAT-2</th>
<th>RADARSAT-2</th>
<th>RADARSAT-2</th>
<th>RADARSAT-2</th>
<th>RADARSAT-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>image 1</td>
<td>image 2</td>
<td>image 1</td>
<td>image 2</td>
<td>image 3</td>
<td>image 4</td>
<td>image 5</td>
</tr>
<tr>
<td>$\sigma_{RI}^2$</td>
<td>$D$</td>
<td>$\sigma_{RI}^2$</td>
<td>$D$</td>
<td>$\sigma_{RI}^2$</td>
<td>$D$</td>
<td>$\sigma_{RI}^2$</td>
</tr>
<tr>
<td>0.12</td>
<td>0.23</td>
<td>0.11</td>
<td>0.21</td>
<td>0.14</td>
<td>0.23</td>
<td>0.15</td>
</tr>
</tbody>
</table>
In order to evaluate the computing performance of the proposed segmentation algorithm, we produced a series of different size test images. These images were created from a single test scene by pixel replication. The time taken by the algorithm to process these data is shown in Table 2.

6.2 Comparison

In order to demonstrate the effectiveness of the proposed segmentation algorithm, we compared it with a traditional edge-based algorithm on the basis of watershed segmentation algorithm (see [Fjortoft et al. 1998] for detailed implementation), which is similar to our GAC model based on ROEWA (MGAC) procedure.

Figure 6 shows the edge-based segmentation results for two RADARSAT-1 images. Quantitative comparison of the performance of the two segmentation algorithms is given in Table 3.

Figure 5: Segmentation results of five RADARSAT-2 images using our method. (a) Original image extracts with initial contours; (b) Detected contours; (c) Segmentation results.
The experimental results demonstrated the following. Firstly, our method is, by visual inspection, better than the edge-based method (watershed algorithm are smaller than those in the watershed algorithm (see Table 3), which verifies the superior segmentation quality of our approach. Thirdly, our method has better performance and is easier to use than the watershed method. In particular, the watershed technique usually needs thresholding to eliminate false edges before the watershed segmentation and needs region merging to acquire reasonable segmentation results after the watershed transformation. In contrast, our method can get final segmentation results directly and needs no pre- and post-processing.

7. Concluding Remarks

In this paper, we have presented a novel geodesic active contour model based on SAR image edge detectors under the criterion of energy minimization. The experimental results obtained by using simulated, and real RADARSAT-1/-2 images show that our segmentation algorithm has several advantages over traditional approaches. Firstly, it can locate the object edges accurately and produce homogeneous segmentation regions. Secondly, it takes less computational time. Finally, it is more robust to initial conditions than the classical Snakes algorithm. The proposed method is limited, however, to handle less than two classes, etc. Designing a more efficient algorithm based on the multigrid method [Papandreou and Maragos 2007] to speed up the convergence would be an interesting avenue for further research. In addition, using the statistical properties of SAR images more explicitly should produce more accurate segmentation.

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References


Authors

Dr. Gangyao Kuang received the B.Sc. and M.Sc. degrees from the Central South University, China, in 1988 and 1991, respectively, and the Ph.D. degree from the National University of Defense Technology (NUDT), China, in 1995. Since 1996, he has been the Co-director of the Remote Sensing Information Processing Laboratory at NUDT, where he has been working on SAR signal and image processing, automatic target detection and recognition, information fusion, and various remote sensing projects. He is currently a Professor in the School of Electronic Science and Engineering at NUDT. He is the author/coauthor of over 200 papers and two books. His current interests include remote sensing, SAR image processing, change detection, SAR ground moving target indication, and the classification of polarimetric SAR images.

Dr. Jonathan Li holds the Ph.D. degree in geomatics engineering from the University of Cape Town, South Africa and he is a full professor in the geomatics program at the Department of Geography & Environmental Management and heading a Remote Sensing and Geospatial Technology research group at the University of Waterloo, Canada. He is also Adjunct Professor of York University, Peking University, Wuhan University, Tianjin University, Hehai University, Changan University, Central South University and China University of Geosciences. He has published over 150 publications including four co-edited books and 5 journal theme issues as well as more than 60 refereed journal articles. His current research interests in SAR remote sensing include SAR image segmentation, feature extraction, object classification and RADARSAT applications in marine and coastal environments such as marine oil spill tracking and shoreline detection. Dr. Li is currently Vice Chair of ICA Commission on Mapping from Satellite Imagery and an Associate Editor of Geomatica.

Dr. Zhiguo He received the B.Sc., M.Sc., and Ph.D. degrees from the National University of Defense Technology, Changsha, China, in 2001, 2004 and 2008, respectively, all in remote sensing information processing. His current research interests include SAR imaging processing, automatic feature extraction from SAR imagery.