# MULTIREGION LEVEL-SET SEGMENTATION OF SYNTHETIC APERTURE RADAR IMAGES

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## ABSTRACT

Due to the presence of speckle, segmentation of SAR images is generally acknowledged as a difficult problem. A large effort has been done in order to cope with the influence of speckle noise on image segmentation such as edge detection or direct global segmentation. Recent works address this problem by using statistical image representation and deformable models.

We suggest a novel variational approach to SAR image segmentation, which consists of minimizing a functional containing an original observation term derived from maximum *a posteriori* (MAP) estimation framework and a Gamma image representation. The minimization is carried out efficiently by a new multiregion method which embeds a simple partition assumption directly in curve evolution to guarantee a partition of the image domain from an arbitrary initial partition. Experiments on both synthetic and real images show the effectiveness of the proposed method.

***Index Terms—*** image segmentation, Gamma distribution, level set, synthetic aperture radar.

## 1. INTRODUCTION

Synthetic Aperture Radar (SAR) instruments have been widely used in the past years for remote sensing applications [1]. Automatic interpretation of SAR images is an important component of many applications domains such as agriculture, urban planning, and geology. A crucial point for SAR image automatic interpretation is the low level step of scene segmentation. Due, in part, to the presence of speckle, which can be modeled as strong multiplicative noise, segmentation of SAR images is generally acknowledged as a difficult problem. Within that domain, a large effort has been done in order to cope with the influence of speckle noise on image segmentation such as edge detection or direct global segmentation.

Edge-based segmentation schemes aim at finding out the transitions between uniform areas, rather than directly identifying them. These schemes are based on edge detection filters developed for SAR images with proper modeling of speckle [2]. It has been shown in [3] that the results of these filters introduce a bias and increase the variance in the estimation of the edge position when the window has not the same orientation as the edge. Furthermore, the problem of forming closed boundaries from separated edge segments given by a filter is difficult and these schemes require postprocessing steps to prevent oversegmentation. Other approaches such as those based on histogram thresholding [4] and region growing [5], have also been developed, but they lead to similar limitations.

Global approaches generally consist in optimizing an energy function depending on the whole image. These approaches start from a given model and let it evolve in order to optimize the considered energy criterion. Recently, a large interest has been devoted to variational methods for image segmentation, particularly those, based on curve evolution and level sets which have been applied mainly to optical images [6]. For SAR images, a region-based active contour scheme is presented in [7]. A contour is iteratively deformed to locate the boundary of a region, guided by a statistical criterion. The scheme was shown to improve on the traditional likelihood ratio filter method. The classical active contour model presents, however, several limitations. First, it discretizes a curve using a set of points and, as a result, topological changes which occur during the evolution of the curve are difficult, if at all possible, to effect. Second, segmentation depends on parameterization and errors in the representation can be significantly amplified during evolution.

Recently, Ayed et al. [8] investigated SAR image segmentation into a given but arbitrary number of gamma homogeneous regions via active contours and level sets. The proposed algorithm consists of evolving simple closed planar curves within an explicit correspondence between the interiors of curves and regions of segmentation to minimize a criterion containing a term of conformity of data to a speckle model of noise and a term of regularization. This led to partitions of the image domain. However, this approach activates all the level sets at each iteration and the complexity of the corresponding PDEs increases with the number of regions.

In this paper, we solve the above problem by investigating an efficient minimization scheme which results in an unambiguous multiregion segmentation. The scheme is based a natural assumption: if a region claims a

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point, it must have the smaller residual according to a certain criterion than other regions who also claim the point. The proposed method consists of minimizing a functional containing an original observation term derived from maximum *a posteriori* (MAP) estimation framework and a Gamma image representation. We describe experiments which verify the method and its implementation.

## 2. DESCRIPTION OF THE MODEL

Let $I:\Omega \to \mathbb{R}^n$ be the intensity SAR image to be segmented, defined on $\Omega \subset \mathbb{R}^2$. When radar senses a large area, the acquired complex signal is the result of several elementary scatters within a resolution cell. For a single-look SAR image, the intensity is given as $I = a^2 + b^2$, where $a$ and $b$ denote the real and imaginary parts of the complex signal. In the case of multilook SAR images, the $L$-look intensity is obtained by averaging the $L$ intensity images. Following the fully developed speckle hypothesis [9], we model the image in each region $R_i$, ($i \in [1, M+1]$) by a Gamma distribution of mean intensity $\mu_{R_i}$ and a number $L$ of looks:

$$p_{\mu_{R_i},L}(I(x)) = \frac{L^L}{\mu_{R_i}\Gamma(L)}\left(\frac{I(x)}{\mu_{R_i}}\right)^{L-1} e^{-\frac{LI(x)}{\mu_{R_i}}} \tag{1}$$

The image in each region $R_i$, ($i \in [1, M+1]$) is therefore characterized by its mean $\mu_{R_i}$ and the number of looks $L$, which we take to be the same for all regions. This model has been extensively used in SAR image applications such as speckle reduction, edge detection [2], [7].

A probabilistic formulation is a powerful approach to deformable models. Deformable models can be fit to the image data by finding the model shape parameters that maximize the posterior probability. The goal of image segmentation is to find a partition of the domain $\Omega$. Consider $I$ that has $M$ regions of interest (ROI): $R_1, R_2, ..., R_M$, and let their complement $R_b$ denote the region of the background. Let the boundary of each region $R_i$ be $\partial R_i$, $i \in [1, M]$. Let $\vec{\gamma}_i$ be a closed planar curve, oriented counterclockwise, that we use as an estimator of $\partial R_i$, $i \in [1, M]$. In this paper, $R_{M+1}$ and $R_b$ are used interchangeably. A MAP framework can be used to realize image segmentation with image information.

We introduce the energy functional $E$ defined by

$$\begin{aligned} E &= -\log p(R_1, R_2, ..., R_i, ..., R_M, R_b | I) \\ &= -\log p(I | R_1, R_2, ..., R_M, R_b) \\ &\quad -\log p(R_1, R_2, ..., R_M, R_b) \end{aligned} \tag{2}$$

where $\log(p(I | R_1, R_2, ..., R_M, R_b))$ is the log-probability of producing an image $I$ given $R_1, R_2, ..., R_{M+1}$, and

$$\log(p(I | R_1, R_2, ..., R_b)) = -\sum_{i=1}^{M+1} a_{R_i} \log \mu_{R_i}$$

here, $\mu_{R_i} = \int_{x\in R_i} I(x)dx \Big/ \int_{x\in R_i} dx$, $a_{R_i} = \int_{x\in R_i} dx$,

and $p(R_1, R_2, ..., R_M, R_b)$ is the joint density function of all the $M$ regions, and modeled as a general boundary smoothness prior:

$$p_B(R_1, R_2, ..., R_M, R_b) = \prod_{i=1}^{M+1} e^{-\alpha\int_{\vec{\gamma}_i} ds}$$

Therefore,

$$E_{M+1} = \sum_{i=1}^{M+1} a_{R_i} \log \mu_{R_i} + \sum_{i=1}^{M+1} \alpha \oint_{\vec{\gamma}_i} ds \tag{3}$$

We consider the simpler case corresponding to $M = 1$ (one region of interest) first. We only restate the analysis result of [8] with the level set representation as follows:

$$\frac{d\phi}{dt} = -\left(\log \mu_{R_1} + \frac{I}{\mu_{R_1}} - \log \mu_{R_b} - \frac{I}{\mu_{R_b}} + \alpha\kappa\right)\|\nabla\phi\| \tag{4}$$

where curve $\vec{\gamma}_1$ is represented implicitly as the zero level set of a function $\phi:\mathbb{R}^2 \to \mathbb{R}$, and $\kappa$ is the mean curvature function of $\vec{\gamma}_1$.

## 3. EXTENTION TO MULTIPLE-REGION SEGMENTATION

In the multiple regions segmentation, we need to segment $M$ regions (ROI) from the background.

The extension of the algorithm to the case of multiple regions ($M \geq 2$) can be achieved without going back to the original formulation and by considering only the final level set evolution equations derived above in the case of two regions. The main difference is that, contrary to the two-region case where a single function $\phi$ could represent two distinct regions (the region being represented by the support of the positive part of $\phi$ and the background—by the support of the negative part), the straightforward extension to multiple-region segmentation requires as many level set functions as there are $M$ regions. Each region will then be represented by the support of the positive part of its corresponding level set function. The resulting evolution equations will consist of a system of coupled partial differential equations. The coupling will naturally follow from the fact that the various level set functions will compete against each other to claim their respective regions.

Consider the family $\{\phi_i : \mathbb{R}^n \to \mathbb{R}\}_{i=1}^{M+1}$ of functions, where the support of the positive part of $\phi_i$ represents the $i$ th region. The initial condition for the evolution equation of $\phi_i$ represents the initial estimate of the $i$ th region. Generally isolated from one another at initialization, the boundaries of these initial regions should be encouraged to grow so as to englobe as many points as possible. Instead of considering competition between region and background in two-region segmentation, we here consider $\phi_i$ to claim point $x$ if $(\log \mu_{R_i} + \frac{I}{\mu_{R_i}})$ is less than some constant $C$. This constant is a decision threshold, which depends on the observation noise in the image. Following (4), the evolution equation for the $\phi_i$ should then initially be:

$$\frac{\partial \phi_i}{\partial t} = -((\log \mu_{R_i} + \frac{I}{\mu_{R_i}}) - C + \alpha\kappa_i)\|\nabla \phi_i\| \quad (5)$$

Eventually, the supports of the positive parts of the functions $\phi_i$ will grow and may overlap. If at some image point $x$ there are exactly two distinct indices $i$ and $k$ for which $\phi_i(x)$ and $\phi_k(x)$ are both positive, then clearly $x$ should be assigned to the one with smaller residual. If, in addition to $\phi_i$, two or more regions compete for the same point $x$, $\phi_i$ should claim $x$ only if by considering $(\log \mu_{R_i} + \frac{I}{\mu_{R_i}}) - (\log \mu_{R_k} + \frac{I}{\mu_{R_k}})$ for all $k$ for which $\phi_k(x) > 0$. The evolution of $\phi_i$ should then be given by:

$$\frac{\partial \phi_i}{\partial t} = -((\log \mu_{R_i} + \frac{I}{\mu_{R_i}}) - \min_{k\neq i, \phi_k(x)>0}\{\log \mu_{R_k} + \frac{I}{\mu_{R_k}}\} + \alpha\kappa_i)\|\nabla \phi_i\| \quad (6)$$

It is important to note that the regions obtained at the steady state of these partial differential equations may not form a partition of the image domain; ambiguities may persist, such as a point simultaneously belonging to two or more regions. Conversely, points of the image domain may not be part of any region. The former case occurs whenever distinct regions explain equally well of a point, while the latter occurs whenever regions in the image are occluded and no region can explain the points.

We solve the above problems here in a simple way. By considering only $M$ functions, ROI, and by further coupling them so as to penalize any overlap of the supports of their positive part, a system of evolution equations for $\{\phi_i\}_{i=1}^{M}$ implementing this constraint is given by

$$\frac{\partial \phi_i}{\partial t} = -\left(\left[(\log \mu_{R_i} + \frac{I}{\mu_{R_i}}) - \min_{k\neq i, \phi_k(x)>0}\{\log \mu_{R_k} + \frac{I}{\mu_{R_k}}\}\right] + \alpha\kappa_i + \beta\{1 - \prod_{j\neq i}\chi_{\{\phi_j<0\}}\}\right)\|\nabla \phi_i\|$$

where $\chi_A$ denotes the indicator function of the set $A$, i.e., $\chi_A(x) = 1$ for $x \in A$ and is $0$ otherwise. The product of all the indicator functions will be $0$ if at least one of them is $0$, that is, if at least one other region overlaps with the $i$ th region. In this case, the partial derivative $\partial\phi_i/\partial t$ is further reduced, thus restricting the growth of $\phi_i$. If, on the other hand, all the indicator functions in the product are $1$, then the partition constraint disappears and the evolution equation becomes equivalent to (6). Such a constraint can be naturally incorporated owing to the level set representation of the regions.

All of the above cases can be summarized in one single evolution equation, given by

$$\frac{\partial \phi_i}{\partial t} = -\left(\max\left\{\left[(\log \mu_{R_i} + \frac{I}{\mu_{R_i}}) - C\right], \left[(\log \mu_{R_i} + \frac{I}{\mu_{R_i}}) - \min_{k\neq i, \phi_k(x)>0}\{\log \mu_{R_k} + \frac{I}{\mu_{R_k}}\}\right]\right\} + \alpha\kappa_i + \beta\{1 - \prod_{j\neq i}\chi_{\{\phi_j<0\}}\}\right)\|\nabla \phi_i\| \quad (7)$$

Here, the $\min$ is defined to be $C$ whenever there is no index $k \neq i$ for which $\phi_k(x) > 0$.

It is important to note that the system of evolution equations thus obtained does not necessarily lead to the MAP estimate of the region segmentation. Indeed, these evolution equations were obtained by generalizing the $M = 1$ case, yet the generalization was done in such a way as to locally reduce to the evolution equations for $M = 1$ in some particular situations. Thus, the solution of proposed evolution equations should yield a reasonable approximation to the original Bayesian estimation problem, since it reduces to Bayesian estimation in the two-region case every time all but two of the level set functions are held fixed.

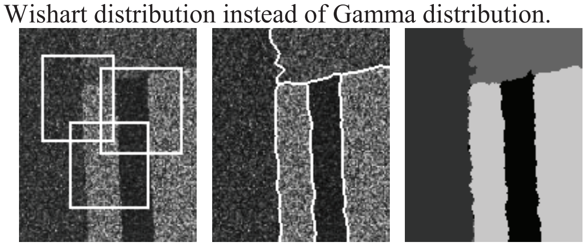
## 4. EXPERIMENTAL RESULTS

In this section, we illustrate the results of the proposed segmentation technique obtained with some synthetic and real SAR images.

To verify the SAR image intensity model and the segmentation method we proposed, we first simulate a 1-look case by the synthetic image of Fig. 1. This image is analogous to the agricultural SAR image of Fig. 3. It consists of three regions (we label rest part of the image as background), as visual inspection can quickly indicate. We simulate the 3-look case by the synthetic image of Fig. 2. It consists of five regions. Fig. 1a and Fig. 2a1, Fig2a2 show the initial position of the evolving curves for the two images, Fig. 1b and Fig. 2b show final position of these curves, and, finally, Fig. 1c and Fig. 2c display the segmented regions represented by their mean gray value at convergence (we label background region as 0 and ROI have been scaled for visual purpose). Initial curves in Fig. 2a1 and Fig2a2 are represented by circles in different radius and in the different positions of the image to illustrate the fact that the result is independent of the initialization. The parameters are set as follows for both images: $\alpha = 0.1$, $\beta = 0.4$, $C = 3$. Results of both segmentation are conforming to expectation. Finally, we apply the algorithm to a 1-look real SAR image of an agricultural area in Ukraine obtained by ERS-1 satellite shown in Fig. 3. We segment the ERS image into two regions. The parameters are set as follows for the ERS image: $\alpha = 0.2$, $\beta = 0.3$, $C = 2$. Fig. 3b shows final position of the curves, and Fig. 3c shows the segmented regions. The result shows an excellent performance of the method.

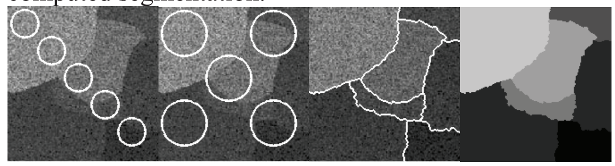
## 5 CONCLUSION

We present a curve evolution algorithm for segmenting a SAR image into a fixed but arbitrary number of Gamma-homogeneous regions. This algorithm consists in evolving curves in order to minimize a statistical criterion. We define an efficient multiregion system of multiple curve evolution equations which minimize the sum of an original observation term derived from MAP estimation framework and a Gamma image representation. The algorithm has been illustrated on both synthetic and real SAR images. The proposed technique can be improved by evolving shape priors of ROI rather than only simplifying the second term of MAP framework to a classical boundary length prior. We are currently addressing this improvement. For polarimetric SAR images, this algorithm may fail due to Gamma image representation assumption. One possible solution is using Wishart distribution instead of Gamma distribution.



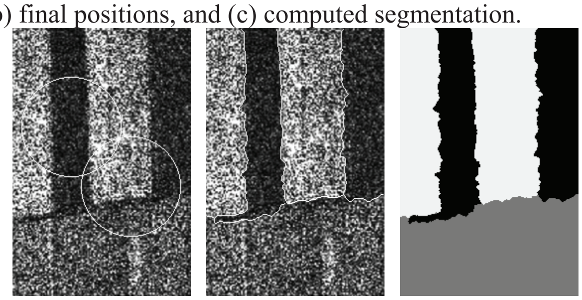
(a) (b) (c)

Fig. 1. Synthetic 1-look speckle image (128 x 154 pixels) of three regions: (a) initial curves, (b) final positions, and (c) computed segmentation.



(a1) (a2) (b) (c)

Fig. 2. Synthetic 3-look speckle image (170 x 173 pixels) of four regions: (a1) initial curves, (a2) another initial curves, (b) final positions, and (c) computed segmentation.



(a) (b) (c)

Fig. 3. ERS SAR image (180 x 270 pixels): (a) initial curves, (b) final positions, and (c) computed segmentation.

## 6. REFERENCES

[1] "Land and sea ERS-1 applications," in Proc. Workshop ESA on ERS Applications, vol. Br-109, London, U.K., 1995.

[2] R. Fjørtoft, A. Lope´s, P. Marthon, and E. Cubero-Castan, "An Optimum Multiedge Detector for SAR Image Segmentation," IEEE Trans. Geoscience Remote Sensing, vol. 36, no. 3, pp. 793-802, 1998.

[3] O. Germain and P. Re´fre´gier, "On the Bias of the Likelihood Ratio Edge Detector for SAR Images," IEEE Trans. Geoscience and Remote Sensing, vol. 38, no. 3, pp. 1455-1457, May 2000.

[4] D.M. Smith, "Speckle Reduction and Segmentation of Synthetic Aperture Radar Images," Int'l J. Remote Sensing, vol. 17, no. 11, pp. 2043-2057, 1996.

[5] R.F. White, "Change Detection in SAR Imagery," Int'l J. Remote Sensing, vol. 12, no. 2, pp. 339-360, 1991.

[6] N. Paragios, O. Mellina-Gottardo, and V. Ramesh, "Gradient Vector Flow Fast Geometric Active Contours," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 26, no. 3, pp. 402-407, Mar. 2004.

[7] O. Germain and P. Re´fre´gier, "Edge Location in SAR Images:Performance of the Likelihood Ratio Filter and Accuracy Improvement with an Active Contour Approach," IEEE Trans. Image Processing, vol. 10, no. 4, pp. 72-77, Jan. 2001.

[8] I. Ben Ayed, A. Mitiche, and Z. Belhadj, "Multiregion Level Set Partitioning of Synthetic Aperture Radar Images," IEEE Trans. Pattern Analysis and Machine Intelligence, vol 27, no. 5, pp. 793-800, May 2005.

[9] J.W. Goodman, Statistical Properties of Laser Speckle Patterns, Chapter on Laser Speckle and Related Phenomena, pp. 9-75, Springer-Verlag, 1975.