A Modified Level Set Segmentation Method for Polarimetric SAR Images

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Abstract

This study investigates the application of the level set method for automated multi-phase segmentation of multi-band and polarimetric synthetic aperture radar (SAR) images. The level set formulation is used to form an energy functional that includes the image statistical information defined on active contours. In addition to the classical Wishart/Gaussian distribution for locating region boundaries, edge information is incorporated into the energy functional to improve the performance of polarimetric data segmentation. An active contour model with an edge indicator is proposed by assuming that the image boundary term follows a Gibbs prior. An empirical parameter setting criterion is developed to ensure that the components of the energy function are in proper proportion. We then investigate the multi-phase extension for energy minimization, and use a piecewise constant model to embed the proposed active contour model. Synthetic and real multi-band polarimetric SAR data are used for verification. The experiments show that our method is superior to another level set method based on the Wishart/Gaussian distribution, in which SAR edge information is not included, particularly for discriminating among low-contrast regions.

1. Introduction

Terrain classification and image segmentation [1] are critical issues in the automated analysis of synthetic aperture radar (SAR) images. Considering the effect of speckle, which is a natural phenomenon in SAR imagery, the applications of SAR data are challenged. To achieve better results, numerous SAR statistical models have been developed to fit SAR images with different resolutions for different observation scenarios. For example, the classic Gaussian/Wishart distribution is typically used to model homogeneous areas. This paper mainly focuses on segmenting homogenous areas. A widely accepted class of techniques for this type of polarimetric SAR image classification and segmentation is usually based on maximum-likelihood (ML) approximation and the complex Gaussian/Wishart distribution. These techniques include the supervised Wishart classifier, unsupervised classifiers with different initialization methods, and segmentation methods such as level set based methods [2] and the spectral graph partitioning method [1]. Pixel-based classification methods do not use spatial information of the scene and pixel neighboring relations. Thus adding a segmentation step for pixel grouping may substantially improve partitioning of the image into homogeneous regions.

In [2], the level set method was investigated for polarimetric SAR image segmentation, where a multi-phase level set method was proposed based on ML approximation and the complex Wishart/Gaussian distribution. This method can guarantee segmentation from an arbitrary initial partition. In addition to the region-based statistical information, the edge is also an important fundamental textural feature. The edge provides immediate information on adjacent homogeneous regions. A popular edge detector for polarimetric SAR images is with the complex Wishart distribution [3]. The edge information is the primary driver in the conventional boundary-based level set methods, such as the classic geodesic active contour (GAC) model [4], which uses an edge stopping indicator to stop the evolving curve on desired boundaries. However, the GAC model cannot be applied to SAR images because the image gradient-based edge detector usually results in significant errors, e.g., a large number of false edges appear in high intensity regions, and a lot of real edges are lost in low intensity regions. Two aspects are mostly concerned in active contour-based methods: the energy functional defined on active contours and the multi-phase extension scheme. In [5], a multi-phase level set framework was proposed by using the Mumford-Shah model, wherein two approximations, namely, piecewise constant and piecewise smooth models, were presented. This multi-phase method uses a few level sets to represent multiple phases, and the problems of vacuum and overlapping can be avoided. In this study, we focus on the level set method for multi-phase segmentation of multi-band polarimetric SAR data. An active contour model is proposed by considering the edge information, which is provided by the polarimetric CFAR edge detector [3]. This edge detector is employed to take account of the reliability of the contour information and to speed up the curve evolution, thereby allowing for computational efficiency. The proposed model consists of two terms: a region-based

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statistical term and a weighted boundary length term. This model is then embedded into the piecewise constant level set framework for multi-phase segmentation.

2. Methodology

We start the analysis from a simple two-region problem. We assume that $\Omega \in R^2$ is the domain of a polarimetric SAR image. Let $P(\boldsymbol{T}|\boldsymbol{V})$ be the probability distribution of $\boldsymbol{T}$ in a homogeneous region and $\boldsymbol{V}$ be a parameter associated with the region statistic. For the image to be partitioned by a curve C, we aim to maximize $P(\boldsymbol{V}_i|\boldsymbol{T})$ by using a Bayesian estimation, which leads to the classical MAP estimator, where $i \in [1, 2]$, and $\boldsymbol{V}_1$ and $\boldsymbol{V}_2$ are the respective statistics inside and outside curve C. Maximizing $P(\boldsymbol{V}_i|\boldsymbol{T})$ amounts to maximizing $P(C|\boldsymbol{T})$. Assume that the partitioning curve C follows a Gibbs prior, i.e., $P(C) = Z^{-1}\exp\big(-u\phi(C)\big)$, where Z and u are normalizing constants, and ϕ is a non-negative given function. We obtain the following energy functional for the whole domain:

$$\begin{aligned} F(C) &= -\ln\big(P(\boldsymbol{T}|C)\big) + u\phi(C) + \ln\big(P(\boldsymbol{T})\big) + \ln(Z) \\ &= \int_{\Omega\backslash C} -\ln\left(\prod_{i=1}^{2} P(\boldsymbol{T}|\boldsymbol{V}_i)\right) d\Omega + u\phi(C) + \int_{\Omega}\Big(\ln\big(P(\boldsymbol{T})\big) + \ln(Z)\Big)\, d\Omega. \end{aligned} \tag{1}$$

$\ln\big(P(\boldsymbol{T})\big)$ and $\ln(Z)$ are constants that are independent of curve C; thus, both are discarded. $\phi(C)$ is a function related to the segmentation boundary C. $\phi(C)$ is often considered as a classic regularizing term defined as the length of curve C, i.e., $\phi(C) = \text{length}(C) = \oint_C ds$. Next we consider the edge indicator in the GAC model [4]. The edge indicator g should be positive on homogeneous regions and nearly zero on sharp edges. A typical g for additive noise is defined on the gradient of an image that is smoothed by a Gaussian kernel function. This gradient-based edge indicator is not suitable for SAR images with multiplicative noise. Moreover, the Gaussian convolution used to smooth the image may blur the edges. Thus, we simply define the edge indicator g as a function of an existing edge image R without considering the Gaussian kernel, as follows:

$$g = \frac{1+k}{1+k(R/T_f)^2}, \tag{2}$$

where k is a constant, R is an edge detector, and T_f is a threshold corresponding to a given probability of false alarms, which is used to measure the reliability of the detected edges. g can be regarded as a weighted edge function for speeding up or slowing down the curve evolution. When g reaches its minimum at the edges with the highest reliabilities, the evolving speed of the curve is low, thus ensuring a gradual change in curve changes to avoid errors. When g reaches its maximum in homogeneous regions, the curve evolves rapidly, thereby accelerating curve propagation. The edge detector R should be robust and efficient to detect edges in images accurately. A CFAR edge detector for polarimetric SAR data was proposed in [3]. This detector is based on the Wishart distribution and can be applied to a wide range of SAR data, including single intensity, dual, and full polarimetric SAR data at multiple bands, as well as their combinations. Let $\phi(C) = g(C) \cdot \text{length}(C) = \oint_C g(C)ds$. Consequently, the two-region partitioning problem shown in (1) from curve C can be rewritten as follows:

$$E_{\text{POL}}(\boldsymbol{V}_1, \boldsymbol{V}_2, C) = u\oint_C g(C)\, ds - \left(\int_{inside(C)} \ln(P(\boldsymbol{T}|\boldsymbol{V}_1))\, d\Omega + \int_{outside(C)} \ln(P(\boldsymbol{T}|\boldsymbol{V}_2)) d\Omega\right), \tag{3}$$

where u is a non-negative parameter. When curve C is right at the edges between two regions, the energy in (3) converges to a global minimum.

Assume Wishart distribution and introduce the level set function [2, 4, 5] for (3) to implicitly present the curve C in a level set function ϕ: $\Omega \to$ R. Associating with the Euler-Lagrange equation and the ML estimation method, we can obtain a dynamic scheme by following the steepest decent method to update the level set function iteratively, as follows.

1) Calculate the SAR edge information R by using the CFAR edge detector introduced in [3], and the edge indicator g by using (2).

2) Initialize the level set function ϕ_i, where i is the iteration number. Let $i = 0$ be the initial value.

3) Keep the level set function ϕ_i fixed, and calculate $\boldsymbol{V}_1$ and $\boldsymbol{V}_2$ by the ML estimation.

$$\boldsymbol{V}_1 = \frac{\int_\Omega \boldsymbol{T}(x,y)\cdot H(\phi_i(x,y))dxdy}{\int_\Omega H(\phi_i(x,y))dxdy}, \qquad \boldsymbol{V}_2 = \frac{\int_\Omega \boldsymbol{T}(x,y)\cdot(1 - H(\phi_i(x,y)))dxdy}{\int_\Omega (1 - H(\phi_i(x,y)))dxdy}. \tag{4}$$

4) Keep the covariance matrices $\boldsymbol{V}_1$ and $\boldsymbol{V}_2$ fixed, Using the associated Euler-Lagrange equation for ϕ_i, the level set evolution equation is obtained as follows:

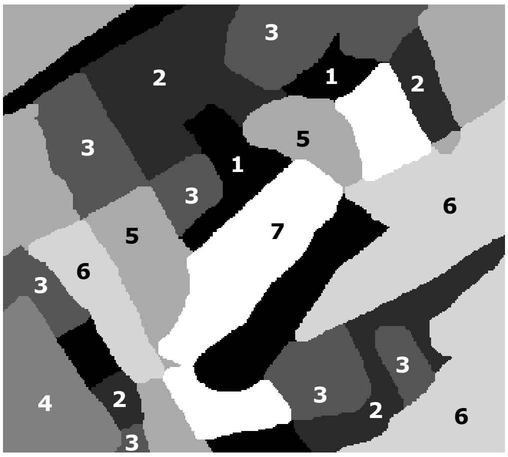
$$\frac{\partial \phi_i}{\partial t} = \delta(\phi_i)\left(\begin{array}{c} u\mathrm{div}\left(g\frac{\nabla\phi_i}{|\nabla\phi_i|}\right) \\ -\left(\left(\ln|\boldsymbol{V}_1| + \mathrm{Tr}(\boldsymbol{V}_1^{-1}\boldsymbol{T})\right) - \left(\ln|\boldsymbol{V}_2| + \mathrm{Tr}(\boldsymbol{V}_2^{-1}\boldsymbol{T})\right)\right) \end{array}\right) \tag{5}$$

where div(·) is a divergence operator, and the corresponding term is the curvature of the normal curve. Then, ϕ_{i+1} is updated by $\phi_{i+1} = \phi_i + dt \times \partial\phi_i/\partial t$, where dt is the time step.

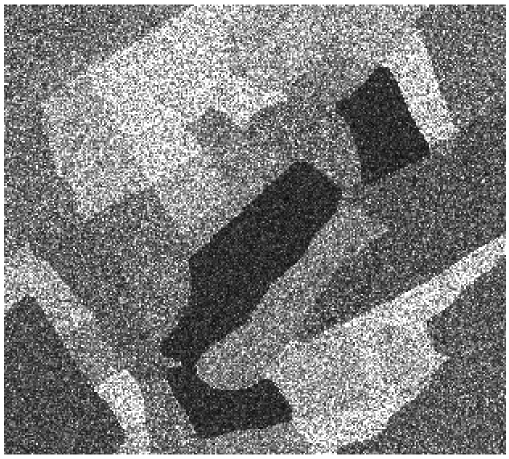
In the evolution of ϕ_i in (5), we replace the common Dirac factor $\delta(\phi_i)$ by $|\nabla\phi_i|$ to speed up the convergence. If we embed the two-phase image energy (3) into the piecewise constant model introduced in [5], we can then realize the multi-phase extension for polarimetric SAR images and multi-band polarimetric SAR images.

3. Experimentation

In this section, we show several representative results of the experiments, and evaluate the segmentation performance and compare it with the Ben Ayed's method in [2]. The differences between the proposed method and the Ben Ayed's method lie in: 1) the Ben Ayed's method did not include the edge information; 2) they adopted different multi-phase extension method. The data used for validation are polarimetric synthetic data, which are generated by using a complex Wishart distribution with four looks and the real covariance matrices obtained by averaging over homogeneous regions in real polarimetric SAR images. Fig. 1 shows the reference map and the span image of the synthesized data. Parameters are set as follows: $dt = 0.5, k = 9, u = 0.218$. The edge detection filter configuration [3] $K_f = \{9, 3, 1, \pi/4\}$ and a false alarm probability $P_f = 10\%$ are used to calculate the edge indicator g. For simplicity, we refer to the proposed method (the proposed model (3) and the multi-phase extension in [5]) as VP, the combination of the proposed model in (3) and the multi-phase extension in [2] as AP, and the segmentation method in [2] as the Ben Ayed's method.



(a)



(b)

Fig. 2. Synthetic data. (a) Synthetic reference map that contains seven classes (class 1, class 2, ... class 7). (b) The span image of synthetic C-band data with four looks.

Fig. 3 provides the final visual comparison. Fig. 3 shows that the segmentation result of the Ben Ayed's method is inferior to those of AP and VP. Moreover, the VP algorithm converges much faster than the Ben Ayed's method, i.e., less iterations are needed. Comparing the results obtained by AP and VP, we observe that although the TSA (Total Segmentation Accuracy) of AP is improved by adding an edge indicator g, its TSA remains inferior to that of VP. The primary reason for this is that the Ben Ayed's multi-phase extension involves all the level set regions for pixel competition at each iteration for a given pixel, thus resulting in the pixel shifting between nonadjacent regions. While with the VP method, a pixel is basically competed between two adjacent regions in each level set function, thus ensuring that the pixel only shifts between neighboring regions. In Fig. 3, the initial and the final curves are displayed in the same color for each method. It shows that both the Ben Ayed's method and AP cannot distinguish class 4 from class 6, and that the former cannot exhibit differences between classes 2 and 3. By contrast, these classes are identified correctly by VP and its segmentation result is quite consistent with the reference map, as shown in Fig. 3(e). Fig. 3(f) illustrates the probability distribution of span for classes 2, 3, 4, and 6. We see that the classes that were barely distinguished by the Ben Ayed's method and AP have similar total backscattering powers.

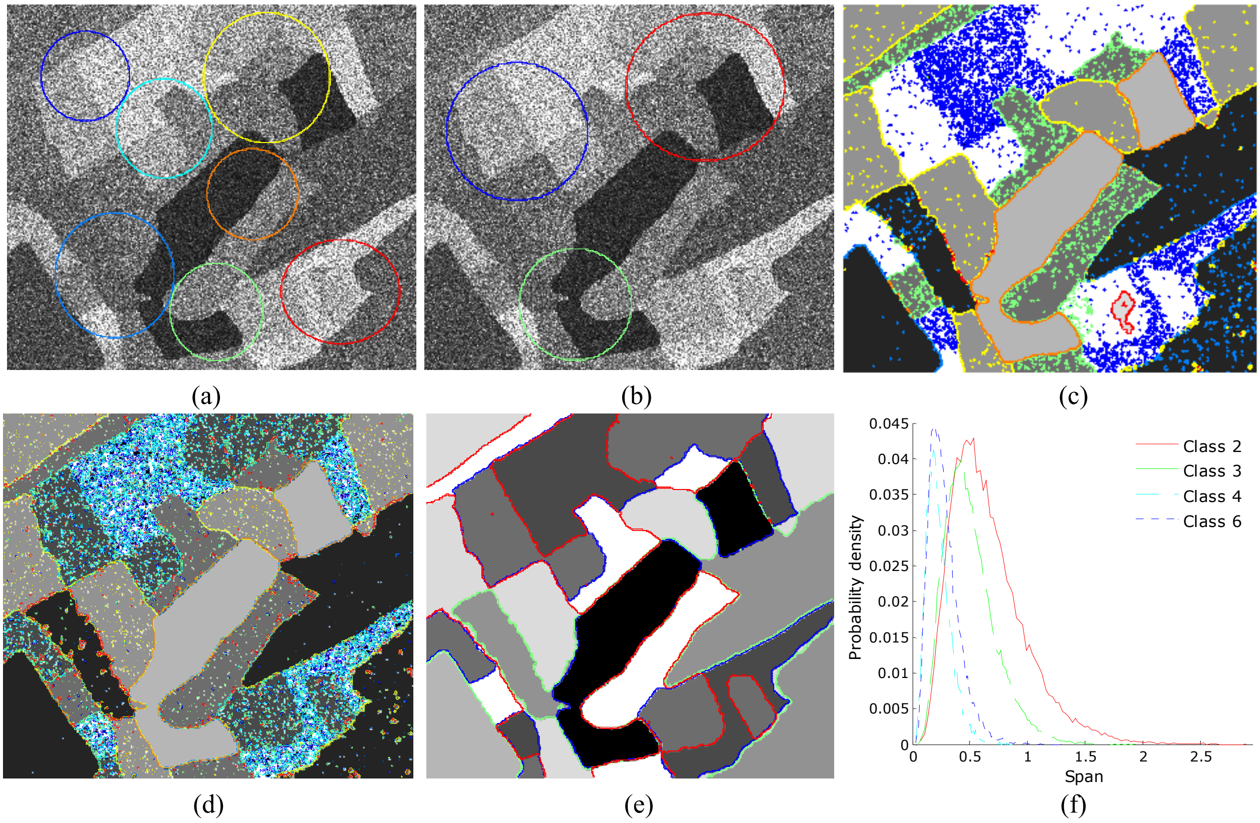


Fig. 3. Comparisons of the final segmentation results using the C-band synthetic data: (a) initial contours for the Ben Ayed's method and AP; (b) initial contours for VP; (c) the result and final curve position of the Ben Ayed's method; (d) the result and final curve position of AP; (e) the result and final curve position of VP. (f) Region distributions of span in C-band for classes 2, 3, 4, and 6, respectively.

5. Conclusion

In this study, we proposed a multi-phase level set method for segmentation of polarimetric SAR data. A CFAR edge indicator was incorporated into an active contour model to detect field boundaries accurately and accelerate curve evolution. By comparing with another Wishart/Gaussian distribution-based level set method, experimental results showed the potential of our method for polarimetric SAR image segmentation. An edge indicator was introduced to improve the active contour model. However, the indicator which is used to extract boundaries is not limited to the form used here. The edge indicator can be constructed as long as it is a monotonically decreasing function that efficiently accounts for image edges. This work also suggests that further improvements can be expected by incorporating more image features (e.g., textural information) into the level set framework.

6. References

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