Segmentation of SAR Images Based on Markov Random Field Model

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Abstract – In synthetic-aperture-radar (SAR) imaging, large volumes of data are normally processed and transmitted over airborne or space-based platforms. The development of fast and robust algorithms for processing and analysis of this type of data is therefore of great importance. It has been demonstrated recently that a Markov-random-field (MRF) model, based on the statistical properties of coherent imaging, provides an ideal framework to describe the spatial correlation within SAR imagery in the presence of speckle noise, which is present in all SAR imagery. When combined with Gibbs-energy-minimization techniques, the MRF-framework has also led to the development of effective and efficient speckle-reducing image restoration algorithms. In this work, the convexity of the Gibbs energy function for SAR imagery is established thereby facilitating the development of a novel image-segmentation algorithm for speckled SAR imagery. The segmentation algorithm is too based on minimizing the Gibbs energy function, which is attained without the need for computationally intensive global optimization techniques such as simulated annealing. A comparative experimental analysis, using real SAR imagery, of the proposed segmentation algorithm against a statistical-thresholding approach is undertaken showing the advantage of the proposed approach in the presence of the speckle noise. Notably, unlike the thresholding technique, the proposed algorithm can be applied to speckled imagery directly without the need for preprocessing the imagery for speckle-noise reduction.

Keywords: Segmentation, Markov random field, synthetic aperture radar, speckle noise.

1 Introduction

The segmentation of remotely sensed images, such as synthetic aperture radar (SAR) imagery, is a key component in the automatic analysis and interpretation of data [1]. Various segmentation methods have been proposed in the literature. Some of the most common are the edge detection [2, 3, 4, 5], the region growing [6], and the thresholding [7] techniques. However, these approaches have well-known flaws. For example, the edge detection technique is very much dependent upon the placement of the initial edge or even knowledge of its position in advance [8]. The region-growing approach is also user-dependent when it comes to growing and merging neighboring small regions [8, 9]. Moreover, segmentation based on thresholding of grey levels is often inappropriate for SAR images because of the presence of speckle noise [10], which is present in all SAR imagery, and it does not exploit the spatial dependency inherent in speckled SAR imagery. Real SAR images are corrupted with an inherent signal-dependent phenomenon named speckle noise. The speckle noise is grainy in appearance and primarily due to the phase fluctuations of the electromagnetic return signals.

In order to address these issues, the Markov-random-field (MRF) method has been investigated [9, 11, 12]. However, it is well known that the MRF-based segmentation approach offers a good performance (by minimizing the associated Gibbs energy function) when the underlying Gibbs energy function is convex [13, 14]. Additionally, the convexity of the energy function guarantees the stability with respect to the input [15, 16, 17] and makes the solution of the optimization problem less sensitive to changes in parameters. We have lately developed a MRF model [18, 19], based on the statistical properties of coherent imaging [20], and shown that it provides an ideal framework for capturing the spatial correlation within SAR imagery in the presence of speckle noise. We have also shown that by utilizing Gibbs-energy-minimization techniques, the MRF-framework can lead to effective and efficient speckle-reduction algorithms. In this work we propose a novel MRF-based segmentation algorithm that exploits the convexity of the Gibbs energy function proposed in [18, 19]. The efficacy of the proposed segmentation algorithm is demonstrated using real SAR imagery and the performance is compared to that offered by a statistical thresholding approach [21].
2 Proposed segmentation approach

2.1 The Markov-random-field model

In this section we revisit germane aspects of the proposed first-order MRF model for speckled images introduced in [18, 19, 22]. The MRF model is represented by an undirected graph, \( G = (V,E) \), that has undirected edges drawn as lines. The set \( V \) of vertices of the graph is \( \{I_k, I_{k_1}, I_{k_2}, I_{k_3}, I_{k_4}\} \) and \( E \) is the set of edges. Two types of cliques are defined for the first-order neighborhood shown in Figure 1(a) and Figure 1(b): the single-cliques and the pair-cliques, as seen in Figure 1(c).

![Figure 1: Neighborhood and cliques.](image)

The conditional probability density function (cpdf) of the intensity \( I_{k_j} \) at point \( k_j \) given the value of the intensity \( I_k \) at point \( k \) is given by Goodman in [20]. In this work we have substituted the global mean, \( \langle I \rangle \), by \( \langle I_k \rangle \), which represents the true intensity image at point \( k \). Within the MRF context, the cpdf of the intensity of the center pixel, \( i_k \), given the four neighbors \( i_{k_1}, i_{k_2}, i_{k_3}, \) and \( i_{k_4} \) is derived and it is given by:

\[
p_{i_k|i_{k_1} \ldots i_{k_4}}(i_k|i_{k_1} \ldots i_{k_4}) \propto \exp\left\{ -\sum_{j=1}^{4} \ln [B(i_k, i_{k_j})] \right\}
- \frac{4}{\sum_{j=1}^{4} \left[ A(i_k, i_{k_j}) \right]} + \ln \left[ \frac{C(i_k, i_{k_j})}{B(i_k, i_{k_j})} \right] \right\}
- 3 \ln [p_{i_k}(i_k)], \quad (1)
\]

where \( A(i_k, i_{k_j}) = [\alpha_{r_{k_k}} \alpha_{r_{k_j}}] i_{k_j} + i_k, \) \( B(i_k, i_{k_j}) = \langle i_k \rangle \times (1 - \alpha_{r_{k_k}} \alpha_{r_{k_j}}) \), and \( C(i_k, i_{k_j}) = 2 \sqrt{i_k i_{k_j}} [\alpha_{r_{k_k}} \alpha_{r_{k_j}}] \).

\( I_0[\cdot] \) is a modified Bessel function of the first kind and zeroth order, and \( \alpha_{r_{k_k}} \) and \( \alpha_{r_{k_j}} \) are, respectively, the coherence factor [20] and the Euclidian distance between the points \( k_j \) and \( k \), and \( \langle i_k \rangle_{k_j} \) is the true intensity at point \( k_j \). The cpdf obtained in (1) has the form:

\[
p_{i_k|i_{k_1} \ldots i_{k_4}}(i_k|i_{k_1} \ldots i_{k_4}) \propto \exp\left\{ -U(i_k, i_{k_1} \ldots i_{k_4}) \right\}, \quad (2)
\]

where \( U(i_k, i_{k_1} \ldots i_{k_4}) = V_{C_1}(i_k) + V_{C_2}(i_k, i_{k_1} \ldots i_{k_4}) \) \( \quad (3) \)

and \( V_{C_1}(i_k) = 3 \ln [p_{i_k}(i_k)]; \) \( V_{C_2}(i_k, i_{k_1} \ldots i_{k_4}) = \sum_{j=1}^{4} \left\{ A(i_k, i_{k_j}) - \ln \left[ I_0 \left[ \frac{C(i_k, i_{k_j})}{B(i_k, i_{k_j})} \right] \right] + \ln \left[ B(i_k, i_{k_j}) \right] \right\} \). Therefore, using the Hammersley-Clifford theorem [23], we derived the energy function or cost function of the MRF to be \( U(i_k, i_{k_1} \ldots i_{k_4}) \). The terms \( V_{C_1}(i_k) \) and \( V_{C_2}(i_k, i_{k_1} \ldots i_{k_4}) \) are, respectively, the single-clique and the pair-clique potential functions. The energy function will be utilized in the segmentation process.

2.2 Segmentation algorithm

Throughout this paper, we assumed the knowledge of the number of classes \( N \). After initialization of the parameters \( \alpha_{r_{k_k}} \) and \( N \), the image to be segmented is scanned and each pixel \( i_k \) is replacing with the class that provides the highest cpdf, i.e.,

\[
(i_k)_{\text{seg}} = \arg \max_{i_k \in CL} P_{i_k|i_{k_1} \ldots i_{k_4}}(i_k|i_{k_1} \ldots i_{k_4}), \quad (4)
\]

\( CL = \{CL_1, \ldots, CL_N\} \) is the set of classes of the image. The maximization in (4) can be rewritten in the form of minimizing the derived cost function \( U(i_k, i_{k_1} \ldots i_{k_4}) \) given in (3):

\[
(i_k)_{\text{seg}} = \arg \min_{i_k \in CL} U(i_k, i_{k_1} \ldots i_{k_4}), \quad (5)
\]

The proposed energy function, unlike other cost functions used in MRF-based segmentation techniques [9, 24, 25], is convex. This property is straightforward to show using the composition rules of convex functions discussed in [13, 14]. As a consequence, the minimization is reached without need for a lengthy and computationally intensive processing such as the simulated annealing [26].

The proposed segmentation algorithm is described entirely by the flowchart shown in Figure 2 and can be summarized as follows. The first step constitutes the initialization stage where the coherence parameter and the number of classes are set. The next step is the segmentation stage: For each pixel \( k \), the intensity, \( i_k \), is run over all possible grey-level values and the one that yields the highest cpdf (given its neighbors) is chosen. The class (in \( CL \)) corresponding to the cpdf-maximizing grey level is then assigned to the \( k \)th pixel. This process is repeated for all pixels \( k \) in the image.

3 Experimental results

In this section, the proposed segmentation described in Section 2.2 is tested on real SAR images [27] and compared to the segmentation based-thresholding approach reported in [7, 28, 21]. One major difficulty in the thresholding approach is the choice of optimal thresholds. In this paper we use a method that maximizes the inter-cluster variance. It is a statistical intensity-histogram-peak picking approach, whose aim is to determine from the histogram the thresholds that maximizes the distance between the peaks obtained.
Figure 2: Flowchart of the proposed segmentation algorithm.

from the histogram. It is entirely based on the data and no parameter is introduced [28]. Two real SAR images are used for the segmentation process [27], which we label by SAR-1 and SAR-2, respectively. We will test each segmentation approach using the speckled SAR images as well as the denoised SAR images in order to see their respectively sensitivity to the speckle noise.

Figures 3 and 5 present the three-class segmentation of SAR-1 and SAR-2 using the thresholding and the proposed segmentation approaches. Figures 3(b) and 5(b) clearly illustrate the poor segmentation results using the thresholding method in the presence of speckle noise. This failure is attributable to the fact that the thresholding segmentation approach does not take into account the spatial correlation within the image, especially in the speckle component. The results are shown in Figures 3(c) and 5(c) showing the performance advantage offered by the proposed algorithm over the thresholding technique.

In order to improve the segmentation process, one can precede it with a speckle removal process. Various speckle reduction algorithms such as the modified-Lee, the enhanced-Frost and the gamma MAP filters [29] have been proposed in the literature. In this work we used a filtering approach based on simulated annealing [19, 18]. The filtered version of SAR-1 and SAR-2 are presented in Figures 4(a) and 6(a), respectively. The results obtained are obviously improved as seen in Figures 4 and 6. In Figure 6(a) on the right side of the image, we can see three trees. In the segmentation using the thresholding approach these tree are not differentiated from the ground. However, for the proposed segmentation approach shown in Figure 5(c), the differentiation is made.

4 Conclusion

In this paper we proposed a novel MRF-based segmentation algorithm for SAR images based on minimizing a proposed convex Gibbs energy function, which is derived from the statistical properties of speckle noise [20, 18, 19]. Experimental comparison of the proposed segmentation algorithm against a common thresholding segmentation technique illustrates two desirable features of the proposed approach. First, unlike the thresholding technique, the proposed algorithm can effectively segment noisy SAR images. The proposed algorithm can therefore be applied to speckled imagery directly without the need for preprocessing the imagery for speckle-noise reduction. Second, the proposed algorithm has the ability to differentiate various targets within an image, which make the resulting segmentation more reliable than the thresholding technique. An extension of this work will focus on having an unsupervised segmentation approach.

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References


[27] Courtesy of Dr. Armin Doerry at Sandia National Laboratories.


Figure 3: (a) Noisy SAR-1. (b) Three-class segmentation of the noisy SAR-1 using the thresholding approach. (c) Three-class segmentation of the noisy SAR-1 using the proposed approach.

Figure 4: (a) Denoised SAR-1. (b) Three-class segmentation of the denoised SAR-1 using the thresholding approach. (c) Three-class segmentation of the denoised SAR-1 using the proposed approach.
Figure 5: (a) Noisy SAR-2. (b) Three-class segmentation of the noisy SAR-2 using the thresholding approach. (c) Three-class segmentation of the noisy SAR-2 using the proposed approach.

Figure 6: (a) Denoised SAR-2. (b) Three-class segmentation of the denoised SAR-2 using the thresholding approach. (c) Three-class segmentation of the denoised SAR-2 using the proposed approach.