Bayesian edge detector for SAR imagery using discontinuity-adaptive Markov random field modeling

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Abstract  Synthetic aperture radar (SAR) image is severely affected by multiplicative speckle noise, which greatly complicates the edge detection. In this paper, by incorporating the discontinuity-adaptive Markov random field (DAMRF) and maximum a posteriori (MAP) estimation criterion into edge detection, a Bayesian edge detector for SAR imagery is accordingly developed. In the proposed detector, the DAMRF is used as the a priori distribution of the local mean reflectivity, and a maximum a posteriori estimation of it is thus obtained by maximizing the posteriori energy using gradient–descent method. Four normalized ratios constructed in different directions are computed, based on which two edge strength maps (ESMs) are formed. The final edge detection result is achieved by fusing the results of two thresholded ESMs. The experimental results with synthetic and real SAR images show that the proposed detector could efficiently detect edges in SAR images, and achieve better performance than two popular detectors in terms of Pratt’s figure of merit and visual evaluation in most cases.

1. Introduction

Synthetic aperture radar (SAR) has the ability to image the areas of interest in all day and all weather conditions, and high-resolution images produced by it can be used for mapping, surface surveillance, earth source monitoring, automatic target recognition (ATR), and so on. Edge detection is a fundamental issue for many SAR image applications ranging from segmentation,1 oil spills detection,2 to ATR.3 It concerns the identification of transitions indicating the boundaries between regions with uniform reflectivity in SAR image.4

Unlike optical imaging sensors, SAR utilizes the coherent imaging principle to yield images, and thus SAR images will be inevitably affected by the coherence speckle noise.5 The multiplicative nature of speckle noise, in the sense that the noise level increases with the magnitude of radar backscattering, makes edge detection in SAR image very different from that in the images corrupted by additive noise.6 In this case, the traditional gradient-based edge detectors such as Sobel edge filter have been proved to be ineffective in detecting edges in SAR image.7 On the other hand, SAR image with low look usually carries heavy speckle noise, making the signal-to-noise ratio (SNR) very low, which also brings about great difficulty in edge detection.

To deal with the problem of correlated speckle noise existing in SAR image, several edge detectors designed specifically
for SAR images have been proposed. These detectors can be roughly divided into two categories, known as ratio-based detectors and multiscale detectors. Representative ratio-based detectors, also called statistical detectors, include ratio of averages (ROA) detector, likelihood ratio (LR) detector and ratio of exponentially weighted averages (ROEWA) detector. These detectors first estimate the local mean reflectivity, and then, combine the ratios of the estimated local mean reflectivity to form the edge strength map (ESM). Generally, the local maxima or minima in SAR image possibly indicate the presence of edges. Unlike the ratio-based detectors relying on the statistical properties of the SAR signals, multiscale detectors utilize the fact that multiscale analysis has the useful property of space and scale localization, so it provides great promise for detecting image feature such as discontinuities at different scales. For example, Alonso et al. proposed a multiscale edge enhancement algorithm that is divided into two steps: edge enhancement and decision, utilizing the fact that speckle noise behaves differently in different scales while the discontinuities could persist over scales. Besides the two kinds of detectors mentioned above, Tourneret et al. proposed a Bayesian off-line edge detection algorithm, wherein the MMSE and maximum a posteriori (MAP) estimators are employed to estimate the edge positions in SAR image. This edge detection algorithm shows superiority to the ROEWA detector, but presents a high computational load due to the implementation of Markov chain Monte Carlo.

Markov random field (MRF) is a promising image analysis tool. It characterizes the contextual or spatial information of an image via the definition of the prior potential functions, and has been applied to various image processing areas such as image restoration and segmentation, texture analysis and despeckling. However, to our best knowledge no application of MRF has been provided for edge detection in SAR image. Hence, in this paper, we propose a Bayesian technique in conjunction with MRF for edge detection in SAR image. The main contribution of this paper is to estimate the local mean reflectivity by maximizing their a posteriori distribution in the Bayesian framework, where in the discontinuity-adaptive (DA) MRF model regularizing ill-posed problems is adopted as the a priori distribution.

The paper is organized as follows. In Section 2, we describe the signal model and statistical property of SAR image. The definition of DA MRF is given in Section 3. The proposed edge detection algorithm for SAR images is presented in Section 4. In Section 5, extensive experiments are shown to verify the efficiency of the proposed detector and conclusions are provided in Section 6.

2. Signal model of SAR image

It is well-known that the radar echo signal received by SAR is the coherent sum of the reflected signals with distributed objects. The complex envelope of the received signal from each resolution cell is the summation of \( N \) scattering echoes in that cell with different amplitudes and phases, resulting from the interaction of electromagnetic waves backscattered by \( N \) different scatterers:

\[
Z(x, y) = \sum_{i=1}^{N} a_i e^{j\phi_i}
\]

where \( a_i \) and \( \phi_i \) are the amplitude and phase of the \( i \)th scatterer, respectively, and assumed independent from each other; \( x \) and \( y \) are the coordinates of a SAR image. \( a_i \) governs the strength and angular distribution of the radiation, and \( \phi_i \) depends on the position of the \( i \)th scatterer in the resolution cell, with respect to the coordinate \( x \). If \( N \) is large, according to the central limit theorem, \( Z \) can be modeled as a complex random variable with independently and identically distributed real and imaginary components, following the zero-mean circular Gaussian distribution, i.e.,

\[
p(Z) = \frac{1}{2\pi\sigma} e^{-|Z|^2/2\sigma^2} \quad (Z \geq 0)
\]

where \( \sigma \) stands for the RCS of the distributed object, the observed signals are the intensity image \( I(x, y) = |Z(x, y)|^2 \) or the amplitude image \( A(x, y) = |Z(x, y)| \). In this study, we only consider the intensity SAR images. There is no difficulty to obtain the probability density function (pdf) of \( Z \) given in Eq. (2)

\[
p(I) = \frac{1}{\sigma} e^{-|I|/\sigma} \quad (I \geq 0)
\]

It is apparent that the amplitude of \( Z \) is dependent not only on the reflection coefficients of the distributed objects but also on the distribution of the scattering centers over the distributed objects. Different positions of scattering centers result in different phases of these elements. For a certain ground object with constant reflection coefficient, the total backscattering signals are mainly contributed by the phases. In general, the random walk process is proper to describe the randomly distributed scatterers, assuming the phases of scatterers are uniformly distributed. Consequently, the observed signals can be seen as the determined radar cross section (RCS) of the ground object which is modulated by a random noise process. This random noise process is referred to as the so-called speckle noise. Assuming the speckle is fully developed and no scatterer is dominant, the observed intensity signal \( I \) can be expressed as the product of two independent signal components

\[
I = \alpha n
\]

and where \( n \) stands for the speckle noise. It is clearly that the distribution of \( n \) is the same as that of \( I \), i.e., negative exponential distribution with mean value equal to one. To reduce the variance of speckle noise, \( L \) independent images are averaged. The resultant observed signals can be written as

\[
I = \frac{1}{L} \sum_{l=1}^{L} I_l
\]

Given Eqs. (2) and (5), we can obtain the pdf of \( I \)

\[
p(I) = \frac{L^L}{I(L)} \frac{\Gamma(L)}{\Gamma(L-1)} \sigma^{-\frac{L-1}{2}} e^{-\frac{L}{\sigma^2}} \quad (I \geq 0)
\]

where \( \Gamma(L) \) is the Gamma function and \( L \) is called the number of looks.

3. DAMRF

Let \( S = \{(x, y)|1 \leq x, y \leq N\} \) denote a rectangular lattice for a 2D image with the size of \( N \times N \), and \( F = \{f_s|s \in S\} \) a family of random variables defined on \( S \). \( F \) is called a Markov random field if the following two conditions are satisfied: (1) positivity
where $\theta > 0$, $\forall f \in F$. (2) Markovianity $p(f_s|f_{s-1}) = p(f_s|f_n)$, where $N_s$ consists of neighboring sites of $s$ and $f_n = (f_s)|s' \in N_s$. The Hammersley–Clifford theorem establishes the equivalence between MRF and Gibbs distribution: $F$ is an MRF defined on $s$ with regard to a neighborhood system $N$ if and only if $F$ is a Gibbs random field on $S$ with regard to $N$.

The Gibbs distribution of $f$ takes the following form

$$p(f) = \frac{1}{Z} e^{-\sum_{c \in \mathcal{C}} V_c(f_c)} = \frac{1}{Z} e^{-\sum_{c \in \mathcal{C}} V_c(f_c)}$$

where $Z = \sum_{f \in F} e^{-\sum_{c \in \mathcal{C}} V_c(f_c)}$ is called the partition function; $T$ is a constant called the temperature controlling the sharpness of the distribution and often takes 1; $U(f)$ the energy function; $V_c(f)$ the clique potential; $C$ the set of all possible cliques defined on the neighborhood system.

An MRF is specified in terms of the joint distribution, which is equivalent to specifying the clique potential functions $V_c(f)$ in the corresponding Gibbs distribution. There exist various MRF models such as Ising MRF, Gaussian MRF, etc. The fundamental differences among MRF models lie in the parameters and the forms of the potential functions which describe the system behavior. In some image processing problems, the blind application of generic smoothness assumption tends to yield undesirable solutions. For example, at the discontinuities of the surface, the uniform smoothness assumption is violated, often leading to oversmoothing at discontinuities. DAMRF model makes it possible to apply the smoothness constraint in image processing while preserving discontinuities.

The DAMRF model is defined in terms of the constrained Euler–Lagrange differential equation. Suppose that the posterior energy $E(f)$ to be minimized is the addition of the conditional energy $U(d(f))$ and the smoothness prior $U(f)$

$$E(f) = U(d(f)) = \frac{1}{b-a} \int_a^b u(f(x)|d(x)) \, dx = U(d(f)) + U(f)$$

$$= \frac{1}{b-a} \int_a^b u(d(x)|f(x)) \, dx + \sum_{n=1}^N \frac{1}{a_n} \int_a^b V_c(f(x)) \, dx$$

where $f$ is the signal to be estimated, $\lambda_n$ a weighting factor, $g^{(0)}(x)$ the potential function, $f^{(0)}(x)$ the $m$th derivative of $f$, and $N$ the highest order to be considered and equals to 1 in our case. Minimizing (8) in the function of $f$ yields the solution that must satisfy the following Euler equation:

$$u_f(f, f') - \lambda \frac{d}{dx} g'(f(x)) = 0$$

where $g'(f')$ is often chosen to be equal to $2f' h(t')$, $h(f')$ is the interaction function, playing an important role in DAMRF-related applications. The following four AIFs listed in Table 1 are often used in practice, and their corresponding shapes are shown in Fig. 1.

### Table 1 Four representative AIFs.

<table>
<thead>
<tr>
<th>AIF1</th>
<th>AIF2</th>
<th>AIF3</th>
<th>AIF4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e^{-r^2}$</td>
<td>$\frac{1}{1+r^2}$</td>
<td>$\frac{1}{1+r^2}$</td>
<td>$\frac{1}{1+r^2}$</td>
</tr>
</tbody>
</table>

Fig. 1 Shapes of four AIFs listed in Table 1.

4. MAP edge detection using DAMRF prior

As we have stated in Section 1, the estimation of the local mean reflectivity which forms the ratios and further determines the ESM is crucial to the ratio-based edge detectors. In this section, we will present a novel edge detector for SAR image. In the proposed detector, we first estimate the local mean reflectivity using MAP criterion, and then, construct two ESMs with ratios from different directions.

4.1. MAP-MRF estimation of local mean reflectivity

In the framework of Bayesian estimation theory, maximizing a posterior probability is one of the most popular statistical optimality criteria. MAP together with MRF model gives rise to a solution to regularize many ill-posed problems in computer vision. According to the MAP criterion, the MAP solution is obtained by maximizing the objective function, i.e., the posterior probability, which is formulated with the product of the prior distribution $p(f)$ of the variable $f$ and the conditional distribution $p(d|f)$ of the observed data $d$.

$$p^* = \arg \max_{f \in F} p(d|f)p(f)$$

In our case, $p^*$ stands for the optimal estimation of the local mean reflectivity whose priori distribution is chosen as the DAMRF model. As for $p(d|f)$, it depends on the relationship between $f$ and $d$. We formulate $d$ by averaging several independent image pixels. Suppose $I_1, I_2, \ldots, I_M$ are from a local sliding window and $d$ is the arithmetic average of those pixels, i.e.,

$$d = \frac{1}{M} \sum_{i=1}^M I_i$$

With Eq. (11) and the pdf of $I_i$, we can obtain the conditional pdf of $d$ given $f$, and its expression is written as follows:

$$p(d|f) = \frac{1}{\Gamma(M)} (f/M)^{-ML} d^{ML-1} e^{-\frac{f}{M} d}$$

It should be noted that $\sigma$ in Eq. (6) is consistent with $f$. Given the conditional probability Eq. (12) and the priori DAMRF model, we can explicitly express the posterior energy $E(f)$ based on which the optimal solution $f^*$ satisfying the corresponding constrained Euler equation can be derived.
First of all, we give the Euler equation, and then, derive the iterative algorithm of obtaining the optimal solution of the local mean reflectivity.

With Eq. (12), and extending Eq. (9) to the 2D case, we can rewrite the Euler equation as follows:

$$\frac{ML}{f(x,y)} - \frac{MLd(x,y)}{f^2(x,y)} - 2\lambda \frac{\partial}{\partial x} f_i h(f_i) - 4\lambda \frac{\partial}{\partial y} f_i h(f_i)$$

$$- 2\lambda \frac{\partial}{\partial y} f_i h(f_i) = 0$$

(13)

where $f_i = \frac{d}{dx} f(x,y), f_i = \frac{d}{dy} f(x,y), f_y = \frac{d^2}{dy^2} f(x,y)$. Using the discrete case of derivative and the first-order difference as an approximation of the first derivative, Eq. (13) can be rewritten as

$$\frac{ML}{f(x,y)} - \frac{MLd(x,y)}{f^2(x,y)} - \lambda \sum_{(x',y') \in N(s)} (f(x',y') - f(x,y))$$

$$- f(x,y)) h(f(x',y') - f(x,y)) = 0$$

(14)

The posterior energy $E(f)$ can be approximated as follows:

$$E(f) = \sum_{s \in S} U(d[s] + \lambda \sum_{s \in S} g(f_i - f_i)$$

(15)

Using the gradient–descent method, we obtain the following updating rule for estimating the local mean reflectivity

$$f_i^{(t+1)} = f_i^{(t)} - 2\mu \left\{ \frac{ML}{f_i^{(t)}} - \frac{MLd(x,y)}{f_i^{(t)}} - \lambda \sum_{(x',y') \in N(s)} (f_i^{(t)} - f_i^{(t)}) h(f_i^{(t)} - f_i^{(t)}) \right\}$$

(16)

where $f_i^{(t)}$ is the $t$th iteration results of local mean reflectivity at site $s$, and $\mu$ a positive constant.

4.2. Calculation of edge strength map

Unlike the ROA and the ROEWA detectors, we propose a combination of two independent ESMs to improve the precision of locating edges. In our proposed edge detector, two independent ESMs are formed with one composed of the horizontal ($0^\circ$) and vertical ($90^\circ$) edge strength components and the other, the left-slanted ($135^\circ$) and right-slanted edge ($45^\circ$) strength components. In the sequel, we will take the horizontal direction as an example to illustrate the procedure of forming the horizontal edge strength component.

Suppose $l(x, y)$ is an arbitrary pixel of interest in a SAR image, and a horizontal local sliding window centered at $(x, y)$ is composed of $2M + 1$ pixels including $f(x, y)$. We average $M$ pixels $l(x, y-M), l(x, y-1)$ in the left half of the local sliding window to obtain a new observed value $d^{(t)}(x, y)$

$$d^{(t)}(x, y) = \frac{1}{M} \sum_{m=1}^{M} l(x, y-m)$$

(17)

In the same way, by averaging $M$ pixels $l(x, y+1), l(x, y+M)$ in the right half of the local sliding window, we can obtain the other observed value $d^{(t)}(x, y)$

$$d^{(t)}(x, y) = \frac{1}{M} \sum_{m=1}^{M} l(x, y+m)$$

(18)

Substituting $d^{(t)}(x, y)$ and $d^{(t)}(x, y)$ into Eq. (16) separately, we obtain two corresponding estimates of the local mean reflectivities $\hat{f}_{MAP}^{(t)}(x, y)$ for the left-horizontal direction and $\hat{f}_{MAP}^{(t)}(x, y)$ for the right-horizontal direction, respectively. The horizontal edge strength component is the minimum of two ratios:

$$r_{HL_{\min}}(x, y) = \min \left\{ \frac{\hat{f}_{MAP}^{(t)}(x, y - 1)}{\hat{f}_{MAP}^{(t)}(x, y + 1)} \right\} \left\{ \frac{\hat{f}_{MAP}^{(t)}(x, y + 1)}{\hat{f}_{MAP}^{(t)}(x, y - 1)} \right\}$$

(19)

The same procedures indicated by Eqs. (17)–(19) are carried out in the vertical, left-slanted and right-slanted directions, and three ratios corresponding to each direction are as follows:

$$r_{V_{\min}}(x, y) = \min \left\{ \frac{\hat{f}_{V_{1}}^{(t)}(x, y - 1)}{\hat{f}_{V_{2}}^{(t)}(x, y + 1)} \right\} \left\{ \frac{\hat{f}_{V_{2}}^{(t)}(x, y + 1)}{\hat{f}_{V_{1}}^{(t)}(x, y - 1)} \right\}$$

(20)

$$r_{L_{\min}}(x, y) = \min \left\{ \frac{\hat{f}_{L_{1}}^{(t)}(x, y - 1)}{\hat{f}_{L_{2}}^{(t)}(x, y + 1)} \right\} \left\{ \frac{\hat{f}_{L_{2}}^{(t)}(x, y + 1)}{\hat{f}_{L_{1}}^{(t)}(x, y - 1)} \right\}$$

(21)

$$r_{R_{\min}}(x, y) = \min \left\{ \frac{\hat{f}_{R_{1}}^{(t)}(x, y - 1)}{\hat{f}_{R_{2}}^{(t)}(x, y + 1)} \right\} \left\{ \frac{\hat{f}_{R_{2}}^{(t)}(x, y + 1)}{\hat{f}_{R_{1}}^{(t)}(x, y - 1)} \right\}$$

(22)

where $r_{V_{\min}}(x, y), r_{L_{\min}}(x, y)$ and $r_{R_{\min}}(x, y)$ are the vertical, left-slanted and right-slanted edge strength components, respectively. With the four ratios shown in Eqs. (19)–(22), one ESM denoted by E1 is formed by taking the magnitude of the horizontal and the vertical edge strength components shown in Eqs. (19) and (20)

$$E1(x, y) = \sqrt{r_{HL_{\min}}^2(x, y) + r_{V_{\min}}^2(x, y)}$$

(23)

The other one denoted by E2 is formed by taking the magnitude of the left-slanted and the right-slanted edge strength components shown in Eqs. (21) and (22)

$$E2(x, y) = \sqrt{r_{L_{\min}}^2(x, y) + r_{R_{\min}}^2(x, y)}$$

(24)

In the ESMs, the local minimum indicates the presence of an edge. By thresholding E1 and E2, we obtain two binary edge maps Edge1 and Edge2 whose elements take 1 representing edge or 0 representing non-edge. The final edge map Edge is the fusion of Edge1 and Edge2:

$$\text{Edge} = \text{Edge1} \cup \text{Edge2}$$

(25)

where $\cup$ represents logical OR operation. Hereafter, the proposed edge detector is named as DAMRF-MAP detector.

4.3. About model parameters

As indicated by Eq. (16), the variation of four parameters, the weighting coefficient $\lambda$, the shape parameter $\gamma$, the convergence factor $\mu$ and the window size $M$. The weight $\lambda$ and the window size $M$ is analyzed briefly as follows.

It is shown in Eq. (16) that the smoothing strength item in Eq. (16) is weighted by the parameter $\lambda$. Hence, the larger the $\lambda$, the more modification of the smoothing strength to the local mean
reflectivity. Parameter $\gamma$ is involved in the AIFs listed in Table 1, and closely relates to the shape of the AIF. In fact, in DAMRF model, there exists a band $(-\sqrt{\gamma}, \sqrt{\gamma})$ within which the smoothing strength $\beta(f) = \frac{1}{\sqrt{1 + f^2}}$ increases monotonically as $f$ increases, and outside that band, the smoothing decreases and becomes zero as $f \rightarrow 0$. That is the reason why DAMRF model can avoid oversmoothing at discontinuity. In our case, we adopt AIF4 whose reflectivity. Parameter 1538 Yuan. Z et al.

edge detection, which are experimentally decided by us. Values of parameters: $l$, $\alpha$, $\beta$, and $M$, in addition to $\alpha$, cannot be determined theoretically, and are still chosen in an ad hoc way.\textsuperscript{18,19} Table 2 gives the suggested values of parameters: $\lambda$, $\gamma$, $\mu$, and $M$ when applied to SAR image edge detection, which are experimentally decided by us.

4.4. Comments on DAMRF-MAP detector

This section illustrates the motivation of designing the proposed detector, and presents some properties of it.

1) The reason why we choose MRF model as the statistical a priori distribution in edge detection lies in that whether a pixel is an edge or not depends not only on itself but also on its neighboring pixels and MRF is the model that is able to model their spatial relationships between points. On the other hand, DAMRF model has the ability to preserve discontinuity, and, thus, it is a more proper MRF model than others when used for edge detection.

2) Whether the updating rule Eq. (16) can converge to the global optimal solution relies on the starting value $f(0)$. There is no general guideline on the selection of the starting value, and we set $f(0) = d$. It is apparent that according to Eq. (11), $f(0)$ is the ML estimation of the local mean reflectivity in the ROA detector. Hence, initializing the start point as the ML estimation of local mean reflectivity guarantees that Eq. (16) could at least give a comparable estimate to the ML estimation in the worst case.

3) In contrast with the ROA and the ROEWA detectors which make a strict assumption of the number of edges in the local window, the proposed detector is free of such an assumption. Thus, the proposed detector is applicable in both monodire and multidirec edges. In terms of the robustness, DAMRF-MAP detector is superior to the ROA and the ROEWA detectors.

4.5. Comparison of computational complexity

To compare the efficiency between different edge detectors, we can theoretically analyze their computational complexities. In this paper, the computational complexity is expressed in terms of the number of addition and multiplication operations. We suppose that one addition consumes CPU time $a_s$ and one multiplication $m_s$. Moreover, let the input image Im be composed of $N_1 \times N_2$ pixels of interest. The computational complexities of DAMRF-MAP detector, ROEWA detector and ROA detector are analyzed as follows.

4.5.1. DAMRF-MAP detector

The computational complexity of DAMRF-MAP detector imposed on one pixel, starting with averaging pixels from eight directions and ending with computing two ESMS, is analyzed as follows. In summary, DAMRF-MAP detector is mainly composed of three parts: averaging, updating local mean reflectivity and computing ESMS. Let the number of elements in neighborhood system $N_1$ be $S$. AIF4 is adopted here. In the first part, averaging pixels from one direction needs $M - 1$ additions and 1 multiplication, and thus, the total runtime is $8(M - 1)a + 8m$ for eight directions. In the second part, computing AIF4 needs 2 additions and 2 multiplications; according to Eq. (16), a total of $24\alpha a + 8(3S + 1)m$ is needed per iteration for eight directions. In the last part, calculating Eqs. (19)-(22) needs 8 multiplications, and Eqs. (23) and (24) 4 multiplications and 2 additions, and thus, a total of $2a + 12m$ runtime is consumed. Hence, to form the ESM in one pixel, the total runtime of DAMRF-MAP detector is $(8M + 24S - 6)a + (20 + 8(3S + 1)T)m$ if the iteration number is $T$.

4.5.2. ROEWA detector

To compute the horizontal edge strength component, ROEWA detector first smoothes Im column by column using the 1-D smoothing filter, and then, employs the causal and anticausal filters to filter the smoothed image line by line. In that process, a total of $6N_1N_2^2 + 4N_1N_2^2$ additions and $4N_1N_2^2 + N_1\sum_{r=1}^{N_2}(|\sum_{i=1}^{N_1}|r + 1 - i| + \sum_{i=1}^{N_1}|r - i|) + 2N_1\sum_{r=1}^{N_2}\sum_{i=1}^{N_1}|c + 1 - j|$ multiplications are involved. Similarly, to compute the vertical edge strength component, a total of $6N_1N_2^2 + 4N_2N_2^2$ additions and $4N_2N_2^2 + N_1\sum_{r=1}^{N_2}(|\sum_{i=1}^{N_1}|c + 1 - j| + \sum_{i=1}^{N_1}|c - j|) + 2N_2\sum_{r=1}^{N_2}\sum_{i=1}^{N_1}|r + 1 - i|$ multiplications are required. Moreover, $4N_1N_2$ multiplications are required to compute the ratios, and $2N_1N_1$ multiplications and $N_1N_2$ additions to compute the ESM.

4.5.3. ROA detector

Let the size of the sliding window be $(2M + 1) \times (2M + 1)$ for ROA detector. To form the horizontal edge strength component, ROA detector first sums $M$ pixels of the left horizontal window and $M$ pixels of the right horizontal window, respectively, and then, computes the ratio of the sums. The above procedures need $2(M - 1)$ additions and 2 multiplications. The same procedures are conducted in the vertical direction and two diagonal directions. Hence, to form the ESM in one pixel, ROA detector needs $8(M - 1)$ additions and 8 multiplications.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$\lambda$</th>
<th>$\gamma$</th>
<th>$\mu$</th>
<th>$M$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suggested values</td>
<td>0.01–0.1</td>
<td>10–100</td>
<td>0–1</td>
<td>5–10</td>
</tr>
</tbody>
</table>

Table 2 Suggested values of four parameters involved in DAMRF-MAP detector.
For the sake of simplicity, we let $N_1 = N_2 = N$. Therefore, the required runtime for DAMRF-MAP detector is $(8M + 24ST - 6)N^2a + [20 + 8(3S + 1)T]N^2m$, while the required runtime for ROEWA detector and ROA detector is $N^2(20N + 1)a + (6N\sum_{m=1}^{N}\sum_{l=1}^{N}|r - l| + 2N\sum_{m=1}^{N}\sum_{l=1}^{N}|r - l| + N^2(8N + 6))m) + 8(M(1)N^2a + 8N^2m$, respectively. For instance, we set $a = m = 1\mu s$, $N = 128$, $M = 8$, $S = 4$, $T = 20$, and the runtime for DAMRF-MAP, ROEWA and ROA detectors is $66.8$, $774.7$ and $1.05$ s, respectively.

5. Experimental results

In this section, we verified the validity of DAMRF-MAP detector using synthetically speckled and real SAR images. Two representative ratio-based edge detectors, ROA and ROEWA, were used to establish the comparison of the performance of the proposed detector.

5.1. Synthetic data examples

A one-dimensional speckled signal is shown in Fig. 2(a), where in the bold solid line indicates the speckle-free signals. Five abrupt changes in intensity representing edges are embedded into the signal. Fig. 2(b−d) shows the ESMs of DAMRF-MAP, ROEWA and ROA detectors, respectively, after being applied to Fig. 2(a). In ESMs, the local minima for DAMRF-MAP and ROA detectors or the local maxima for ROEWA detector imply the presence of edges. From Fig. 2(b) and (c), we can see that in ESM of each detector, the local minima or maxima representing the true positions of edges exist, demonstrating that three detectors can correctly indicate the edges of the signals in Fig. 2(a). But by carefully observing

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Pratt’s figure of merit of the proposed DAMRF-MAP, ROEWA, ROA detectors with varying window size, obtained on simulated speckled image ($10^{-3})$.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detector</td>
<td>Window size</td>
</tr>
<tr>
<td>DAMRF-MAP</td>
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<tr>
<td>ROEWA</td>
<td>451</td>
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<td>ROA</td>
<td>543</td>
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<table>
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<tr>
<th>Table 4</th>
<th>Pratt’s figure of merit of the proposed DAMRF-MAP, ROEWA, ROA detectors, obtained on simulated speckled images with different looks ($10^{-3})$.</th>
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<tr>
<td>Detector</td>
<td>Look</td>
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<td>ROEWA</td>
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</tr>
<tr>
<td>ROA</td>
<td>471</td>
</tr>
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</table>

Fig. 2 Comparison of three detectors on one-dimensional simulated signal after being applied to (a). The y-coordinates of (b)−(d) denote the ESM of the edge detectors.

Fig. 3 Simulated speckled image.
Fig. 4  Results of edge detection obtained on “airport” image.

Fig. 5  Results of edge detection obtained on “mountain” image.
the ESM of ROEWA detector, i.e. Fig. 2(c), we can find that in the surrounding of the first and the last edge positions, local maxima whose edge strength is comparable to that of the true edge point appear, confusing identification of the true edges and giving rise to false edges. In contrast, as shown in Fig. 2(b) and (d), the minimum of each position of true edge is one and only, meaning that no false edges will be produced. Hence, although three detectors can exactly locate the position of the true edges, DAMRF-MAP and ROA detectors yield less false edges than ROEWA detector by judging from Fig. 2. In this situation, the ROA detector shows superiority to the ROEWA detector, which can be partly attributed to the monoedge circumstance of the signals. What is more, since DAMRF-MAP detector is not restricted by the monoedge or multiedge assumption, it could achieve better performance than the ROEWA detector confined by the multiedge assumption in this case.

Another simulated image with size of $163 \times 163$ and its speckled version with 10-look simulated speckle noise are shown in Fig. 3(a) and (b), respectively. When synthetically speckled images are considered, we utilize Pratt’s figure of merit (PFoM)\(^\text{20}\) to quantitatively evaluate the performances of edge detectors, and its definition is given by

$$P = \frac{1}{\max\{N_{ID}, N_{DE}\}} \sum_{i}^{\text{max}} \frac{1}{1 + z d_{i}^{2}}$$

where $N_{ID}$ and $N_{DE}$ are the number of ideal and detected edge pixels, respectively; $z$ is a calibration constant, and we set $z = 1$; $d_{i}$ is the distance between a pixel declared as edge and the nearest ideal edge pixel. PFoM approaching 1 means perfect edge detection performance for an edge detector. Edge detectors (ROA, ROEWA and DAMRF-MAP) were tested on Fig. 3(b). Table 3 shows the results by applying three detectors to Fig. 3(b) in the case of different window sizes. In the situation of small window size, DAMRF-MAP detector is inferior to the ROA and ROEWA detectors. With the window size increasing, DAMRF-MAP detector gives better results than the ROA and ROEWA detectors. Table 4 shows the results by testing different detectors on simulating speckled images with different looks. We can find that DAMRF-MAP detector outperforms ROA and ROEWA detectors.
detectors in most cases. Table 4 also shows that for all detectors, their PFoM becomes large as the look increases. This is due to the fact that speckle noise becomes less significant with look increasing, and thus, it has less effect on edge detection.

5.2. Examples of real SAR images

Real SAR data were used to test and compare the performance of different detectors. Unfortunately, only visual assessment is available when real SAR images are considered. Fig. 4(a) shows a portion of an airport SAR image with the size of 704 × 690, resolution of 0.5 m, eight-bit and single-look, imaged at X-band with VV-polarization and denoted by “airport” image. Fig. 5(a) shows a mountain SAR image with the size of 1182 × 921, resolution of 1 m, eight-bit and single-look, imaged at X-band with VV-polarization, and denoted by “mountain” image.

Figs. 4(b) and 5(b) show the results of edge detections obtained with the ROA detector. Figs. 4(c) and 5(c) show the results of edge detections obtained with the ROEWA detector. It is clear that both detectors can effectively detect out the true edges, along with some false alarms. Figs. 4(d) and 5(d) show the results of edge detections obtained with the DAMRF-MAP detector. We can conclude that in terms of the amounts of the pixels of the false edges and the connectivity of the true edges, DAMRF-MAP detector performs favorably compared with the ROA and ROEWA detectors. In both experiments, according to Table 2, we set experimentally the parameters \( \lambda, \gamma, \mu \) and \( M \) to \( \lambda = 0.08, \gamma = 25, \mu = 0.8, M = 8 \), respectively, when DAMRF-MAP detector operated on real SAR images.

ESM can help us gain further insight into the edge detection results shown in Figs. 4(b and c) and 5(b and c). Hence, we give the ESMs of ROA, ROEWA and DAMRF-MAP detectors, as shown in Figs. 6(a–d) and 7(a–d) wherein we rely on color indicating edge strength to differentiate edge points from non-edge points. ESMs corresponding to ROA detector are shown in Figs. 6(a) and 7(a) where the dark points colored by blue most possibly belong to edges. We could see clearly that true edges in addition to a lot of points belonging to non-edges are labeled with blue color. Hence, some false alarms are highly likely to be detected out by ROA detector, as shown in Figs. 4(b) and 5(b). ESMs corresponding to ROEWA detector are shown in Figs. 6(b) and 7(b), where the bright point indicates the presence of an edge. In non-edge areas, the
color is uniform, and thus, few false edges will be detected out in these areas, which is in agreement with the results shown in Figs. 4(c) and 5(c). ESMs corresponding to DAMRF-MAP detector are shown in Figs. 6(c and d) and 7(c and d), wherein the blue color indicates the presence of edges. As shown in both ESMs, most true edges are clearly displayed by blue color. In non-edge areas, points are colored either by yellow or by red. They are less likely to be labeled as edges as their edge strength is lower than that of the blue points. It is worthy of noting that DAMRF-MAP detector with two mutually complementary ESMs can avoid loss of true edges when detecting edges in the sense that two ESMs make full use of the directional information of edges.

All edge detection algorithms are written in nonoptimized Matlab codes and run on a dual Intel @ 1.60 GHz CPU with 512 RAM memory. The execution times of DAMRF-MAP, ROEWA, ROA detectors, which were performed on the “airport” image, are 288.96, 471.41, and 28.87 s, respectively. The execution times of DAMRF-MAP, ROEWA, ROA detectors, which were performed on the “mountain” image, are 655.21, 1099.72, and 69.79 s, respectively.

6. Conclusion

In this paper, we have verified the effectiveness of incorporating the priori model of the local mean reflectivity into SAR image edge detection. The main characteristics of the proposed edge detection algorithm lie in two aspects: the priori information of the local mean reflectivity is modeled with the DAMRF and its estimation is done using MAP criterion, which distinguishes this algorithm from the conventional ratio-based edge detectors. However, its limitation is also apparent: although in favor of alleviating the load of complex parameter estimation during estimating the local mean reflectivity, the parameters involved in the proposed algorithm cannot be determined automatically, which to some degree degrade the adaptability of the proposed algorithm. To solve this problem, more appropriate MRF models could be considered when statistically modeling the a priori information of the local mean reflectivity.

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References


