SPECKLE MODELING AND REDUCTION IN SYNTHETIC APERTURE RADAR IMAGERY

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ABSTRACT

A new mathematical framework for modeling speckled imagery is introduced based on embedding the spatial correlation properties of speckled imagery, obtained from statistical optics, into a Markov-random-field (MRF) framework. The model is then used to perform speckle-noise reduction through the utilization of a global energy-minimization algorithm, which consists of simulated annealing in conjunction with the Metropolis sampler algorithm. Comparative experimental results using both simulated as well as real synthetic-aperture-radar (SAR) imagery show that the proposed speckle-reduction technique outperforms existing speckle-noise filtering methods. This success is attributable to the ability of the proposed model to capture the physical spatial statistics of speckle within the confines of a MRF framework.

1. INTRODUCTION

Synthetic-aperture-radar (SAR) is an imaging system that uses coherent radiation to create images. The benefit of SAR over non-radar imaging systems is that it does not rely on an external source. As an active system, SAR emits its own radiations and remains effective independently of weather or daylight conditions. However, this autonomy comes with a higher susceptibility to speckle noise [1]. Grainy in appearance, this signal-dependent speckle noise is primarily due to the phase fluctuations of the electromagnetic returned signals and it is one of the main factors plaguing the performance of SAR imaging system [2].

A large variety of speckle reduction techniques have been proposed in the literature. Among them are the modified Lee filter [3], the enhanced-Frost filter [4], and the approach based on *Markov-random-fields* (MRFs) [2]. These approaches assume a multiplicative model for the speckled image intensity hence each observed image pixel is the product of the noise-free image pixel with the noise [5]. The capability of MRFs to model spatially correlated and signal-dependent phenomena makes them an excellent choice for modeling speckled images. However, exiting MRF-based methods for speckle are not derived from the physical statistical properties of speckle.

In this paper, the multiplicative model is not assumed; instead, we assume that the observed speckled intensity image is one of the configurations of our MRF model whose high energy has to be reduced through de-noising. We derive a novel MRF model for speckled imagery based on the spatial-correlation properties of speckle, which are obtained from the literature on statistical optics [1]. More precisely, we incorporate into the MRF model the joint conditional probability density function (cpdf) of the speckled intensity of any two points. With the availability of this MRF model, the noise reduction of SAR images is undertaken using a global energy-minimization algorithm based on using simulated annealing (SA) [6, 7] in conjunction with the Metropolis sampler [8].

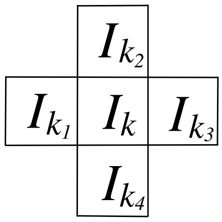

Fig. 1. Neighborhood of the pixel k according to the first-order MRF.

2. FIRST-ORDER MRF SPECKLE MODEL

The goals in this section are to obtain the cpdf of the center pixel intensity given the four neighbors (see Fig. 1) and to derive the energy function of the MRF model. Two types of cliques are extracted from Fig. 1: the single-clique and the pairwise-clique. A single-clique, C_1, is simply any individual pixel in the image; a pairwise-clique, C_2, is a set of any two vertically adjacent or horizontally adjacent pixels.

The extended description of what follows can be found in a technical report [9]. Here, we only present the key results. It can be shown that 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} takes the following form:

$$p_{I_k|I_{k_{1\ldots4}}}(i_k|i_{k_{1\ldots4}}) = \exp\Bigg\{-\sum_{j=1}^{4}\ln\left[B(i_k,i_{k_j})\right] - \sum_{j=1}^{4}\Big\{\frac{A(i_k,i_{k_j})}{B(i_k,i_{k_j})} + \ln\Big(\mathcal{I}_0\big[\frac{C(i_k,i_{k_j})}{B(i_k,i_{k_j})}\big]\Big)\Big\} - 3\ln\left[p_{I_k}(i_k)\right]\Bigg\}, \quad (1)$$

where $A(i_k,i_{k_j}) = |\alpha_{r_{kk_j}}|^2 i_{k_j} + i_k$, $B(i_k,i_{k_j}) = (i_t)_k \times (1-|\alpha_{r_{kk_j}}|^2)$, and $C(i_k,i_{k_j}) = 2\sqrt{i_k i_{k_j}}|\alpha_{r_{kk_j}}|$. Here, $\mathcal{I}_0[\cdot]$ is a modified Bessel function of the first kind and zero-th order, and $\alpha_{r_{kk_j}}$ and $r_{k_i k_j}$ are, respectively, the coherence factor [1] and the Euclidian distance between the points k_i and k_j, and $(i_t)_{k_j}$ is the true intensity at point k_j. The cpdf obtained in (1) has the form

$$p_{I_k|I_{k_{1\ldots4}}}(i_k|i_{k_{1\ldots4}}) = \exp\{-U(i_k,i_{k_{1\ldots4}})\}, \quad (2)$$

where $U(i_k,i_{k_{1\ldots4}}) = V_{C_1}(i_k) + V_{C_2}(i_k,i_{k_{1\ldots4}})$ and

$$V_{C_1}(i_k) = 3\ln\left[p_{I_k}(i_k)\right];\ V_{C_2}(i_k,i_{k_{1\ldots4}}) = \sum_{j=1}^{4}\Big\{\frac{A(i_k,i_{k_j})}{B(i_k,i_{k_j})} - \ln\Big[\mathcal{I}_0\big[\frac{C(i_k,i_{k_j})}{B(i_k,i_{k_j})}\big]\Big] + \ln\left[B(i_k,i_{k_j})\right]\Big\}.$$

From the Hammersley-Clifford theorem [11], the energy function is identified to be $U(i_k, i_{k_{1\ldots4}})$. The terms $V_{C_1}(i_k)$ and $V_{C_2}(i_k, i_{k_{1\ldots4}})$ are, respectively, the single-clique and the pairwise-clique potential functions. The above energy function will be utilized in the speckle reduction process.

3. SPECKLE REDUCTION APPROACH

In this section, we describe the proposed speckle reduction approach, which uses the SA approach with the *Metropolis sampler* (MS) [8] and incorporates the energy function found in Section 2. A narrative description of the proposed approach is given below followed by a detailed flowchart.

The de-noising process essentially works as follows: For each pixel of the image, an initial test, termed the uniformity test, is performed to determine if the pixel is a candidate for de-noising. This test is done by calculating the intensity variability within a 3×3 window W_k centered about the pixel in question (the details are given in Fig. 2). The test also looks for the presence of lines, which may results in high intensity variability that is not attributed to the noise. Low variability in intensity or high variability in the presence of lines (within a W_k neighborhood of the pixel) are indicative of relative homogeneity, which implies, in turn, the "absence" of noise. In such a case, the pixel's intensity is left unaltered and we move to the next pixel. On the other hand, if the intensity variability is high and no lines are detected, the pixel will be subjected to the *simulated annealing-Metropolis sampler* (SA-MS) procedure for de-noising. The SA-MS works by updating the pixel's intensity according to the energy function whose temperature T is allowed to gradually decrease [2, 6]. In particular, an energy difference, ΔU, is calculated between the energies before and after the pixel's intensity is updated with a candidate intensity. This energy difference is then used to accept or reject the pixel's candidate intensity based on a rejection/acceptance sampling scheme. Once the update step is completed for a pixel, the next pixel is considered and handled similarly and the entire procedure is repeated until all pixels in the image are exhausted. Note that the uniformity test described above also serves as a stopping criterion and mechanism for the SA-MS algorithm. The entire denoising algorithm is shown in Fig. 2. Note also that steps 2-4 constitute one iteration of the SA-MS scheme. The test at the end of Step 2 constitutes a reliable criterion (based on our experience) to assess when to end the update of the intensities and hence gives us a stopping criterion.

4. EXPERIMENTAL RESULTS AND ANALYSIS

The speckle reduction algorithm described in Section 3 is now applied to a SAR image. Different alternative speckle-reduction filters, including the Frost [4], the modified-Lee, the enhanced-Frost and the gamma MAP filters [3], have been tested and the best results were obtained with the enhanced Frost. We therefore compare the performance of the proposed method to that of the enhanced-Frost. The metric used to assess the quality of the speckle reduction is the *effective number of looks* (ENL) [2]. It is often used to estimate the speckle noise level in a SAR image. The higher the parameter the lower the speckle noise in the area will be. It is obtained by using the mean and variance intensity over a uniform area. The noisy image SAR_{noisy} (of size 700×700 pixels) is shown in Fig. 3(a). The image shown in Fig. 3(b), called $SAR_{\text{enh-Frost}}$, is the filtered version of SAR_{noisy} using

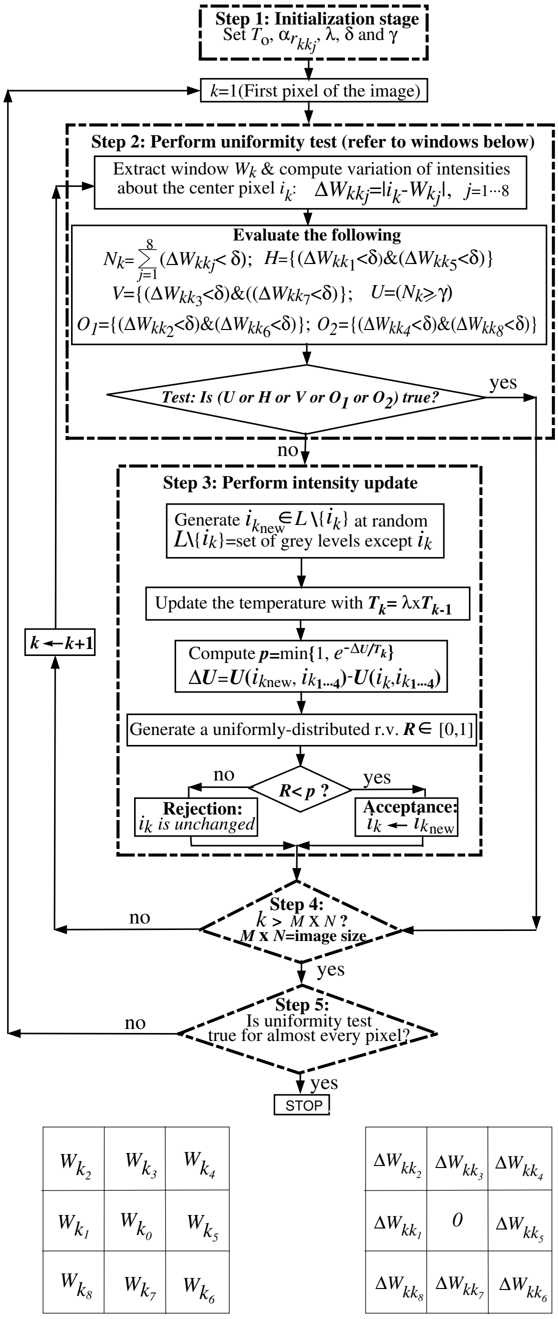

Fig. 2. Flowchart of the speckle reduction proposed approach. Note that T_0 is the initial temperature, $\alpha_{r_{kk_j}}$ is the coherence factor, the parameter λ controls the cooling scheme, the parameter δ is the threshold for line or noise detection, and the parameter γ is the threshold number of pixels within the window W_k of size 3×3 centered in i_k whose variations are below δ. The parameter N_k is the number of pixels within W_k whose intensities are similar (less than δ apart) to the intensity of the center pixel; U, H, V, O_1 and O_2 are the uniform-neighborhood test, the horizontal line test, the vertical line test, the first oblique line test and the second oblique line test, respectively. Also shown is the window W_k centered on the kth pixel (left) and the corresponding window after subtraction of i_k (right).

the enhanced-Frost filter. Finally, Fig. 3(c) shows the de-noised version using the proposed algorithm after 80 iterations. The parameters of the MRF model are set on a case-by-case basis. In this paper, the best results were obtained with $T_0 = 10^{-4}$, $\alpha_{r_{kk_j}} = 0.9$, $\lambda = 0.99$, $\delta = 5$, and $\gamma = 4$. Based on the ENL, after 14 iterations, the proposed approach performs better than the enhanced-Frost (see Table 1). Besides, according to the stopping criterion (Section 3), after the 80th iteration, the algorithm stops.

Let us now analyze and compare the image degradation (blur) due to the filtering process. Consider the bright "cross" in the middle of SAR_{noisy}. At first glance, the "cross" may seems to have a reduce resolution in Fig. 3(c) in comparison to Fig. 3(b). However, after zooming in (see Fig. 4), it is evident that the proposed approach does not affect the noise-free area (i.e., the bright "cross"), and de-noises the rest. In contrast, the enhanced-Frost is more blurred in the noise-free zone and therefore, the proposed approach better preserve the edges. Another illustration of this feature of the proposed technique is seen in Fig. 5, which represents an approximate profile of the point-spread-function (PSF) obtained by observing a bright line in Fig. 3(a) and the results after speckle reduction. It can be seen that the proposed approach has preserved the initial peak more faithfully than that rendered by the enhanced-Frost filter. The same trend is observed in Fig. 6(a)-(b), which represents another noisy image with $ENL = 3.07$ and its filtered proposed version after 60 iterations with $ENL = 10.53$, respectively. For this example, the enhanced-Frost yields an $ENL = 10.39$ (figure not included here for brevity). Further experimental results (not included here for brevity), including those corresponding to simulated SAR imagery, can be found in [9, 10].

Three main reasons may explain the improved performance of our technique. First, the intrinsic spatially correlated and signal-dependent nature of speckle noise makes the MRF framework a natural choice for speckle modeling. Second, the SA-MS, being an iterative method, allows a gradual and adaptive noise removal compared to the standard methods [2]. Third, the energy function used in the SA-MS is derived according to the physical model of the speckle, which, in turns, leads to a reliable speckle reduction.

Due to the computational complexity of the SA-MS algorithm, a more efficient version of the speckle de-noising method, within the same MRF framework, has also been developed showing comparable results. The new method is based on an optimal estimate of the true image intensity, in the sense of minimizing the MSE, and it is given by the conditional expectation of a pixel given its four neighbors. This alternate approach takes on Matlab approximately 5 minutes yielding $ENL = 8.23$ (using only one iteration!), compared to the SA-MS algorithm, which takes approximately 66 minutes to yield $ENL = 8.10$ (using 14 iterations).

	ENL
Noisy SAR	2.66
Enhanced-Frost version	8.08
Proposed approach after the 14th iteration	8.10
Proposed approach after the 50th iteration	11.63
Proposed approach after the 80th iteration	12.21
Proposed approach after the 100th iteration	12.24

Table 1. Speckle reduction results. Note that the higher the ENL the better is the speckle reduction.

(a)

(b)

(c)

Fig. 3. (a) The original noisy image SAR_{noisy}; (b) de-noised image $SAR_{\text{enh-Frost}}$ using the Enhanced-Frost filter; and (c) the de-noised image using the proposed approach (80 iterations).

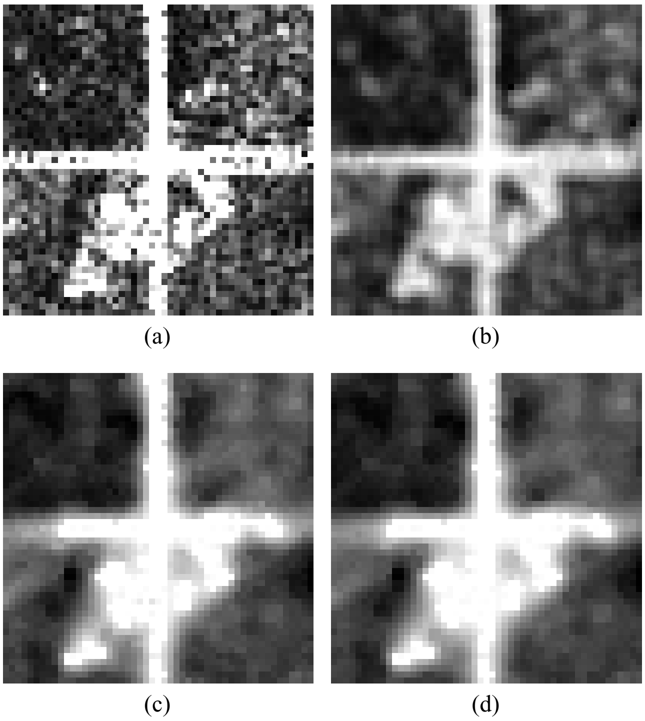

Fig. 4. A zoomed version of: (a) SAR_{noisy}; (b) $SAR_{\text{enh-Frost}}$; (c) de-noised image after 50 iterations; (d) after 80 iterations.

5. CONCLUSION

The main contributions of this paper can be summarized as follows. First, we presents a novel model of speckled imagery in the context of MRFs. Second, the model is used together with the SA-MS algorithm to reduce the speckle in SAR imagery. Third, we introduced a stopping criterion for the SA-MS algorithm in order to have an objective assessment of the convergence of the algorithm and avoid over-smoothing images. Experimental results using real SAR imagery as well as simulated imagery (the latter are not included here for brevity) indicate that the proposed de-noising approach outperforms the enhanced-Frost filter in that it yields improved speckle noise reduction, measured by the ENL parameter, while preserving spatial features.

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6. REFERENCES

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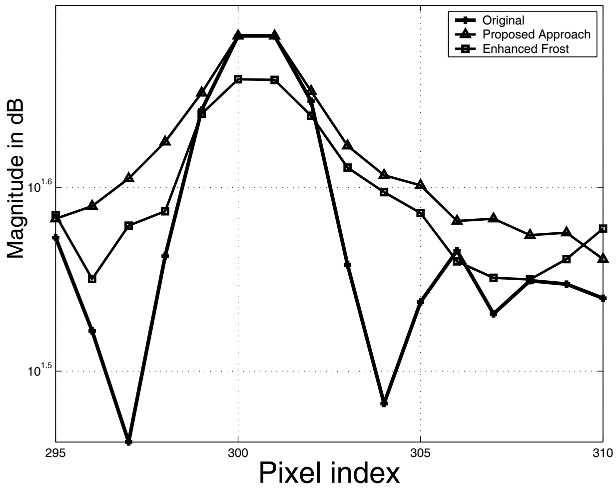

Fig. 5. The original PSF-like curve (+) and its output using the enhanced-Frost (□) approach and after 50 iterations of the proposed approach (△).

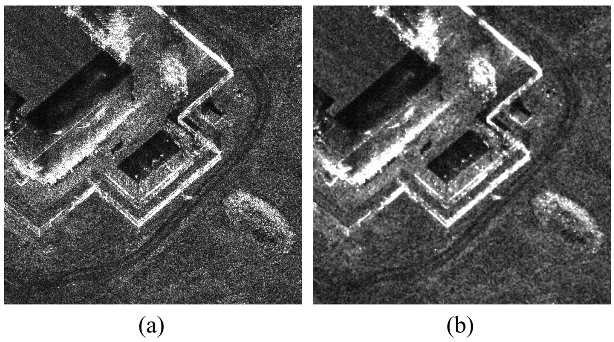

Fig. 6. (a) Second noisy Image (ENL=3.07). (b) Filtered version using the proposed approach (60 iterations, ENL= 10.53).

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