반복 적응법에 의한 SAR 잡음 제거

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Adaptive Iterative Depeckling of SAR Imagery

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Abstracts

In this paper, an iterative MAP approach using a Bayesian model based on the lognormal distribution for image intensity and a GRF for image texture is proposed for despeckling the SAR images that are corrupted by multiplicative speckle noise. When the image intensity is logarithmically transformed, the speckle noise is approximately Gaussian additive noise, and it tends to a normal probability much faster than the intensity distribution. The MRF is incorporated into digital image analysis by viewing pixel type s as states of molecules in a lattice-like physical system defined on a GRF. Because of the MRF-GRF equivalence, the assignment of an energy function to the physical system determines its Gibbs measure, which is used to model molecular interactions.

The proposed adaptive iterative method was evaluated using simulation data generated by the Monte Carlo method. In the extensive experiments of this study, the proposed method demonstrated the capability to relax speckle noise and estimate noise-free intensity.

1. Introduction

Speckle noise is supposed to be dependent on the signal intensity in the sense that the noise level increases with the brightness. A simple statistical model based on multiplicative noise (Dainty, 1984) has been often used for the speckle reduction. Many adaptive filters have been developed to reduce multiplicative noise in SAR images by taking local statistics in order to distinguish between homogeneous regions and edges. The best-known filters include the Lee filter (Lee, 1986), Frost filter (Frost *et al.*, 1982), Kuan filter (Kuan *et al.*, 1985) and Gamma filter (Lopez *et al.*, 1993). The Frost filter was designed as an adaptive Wiener filter that assumed an autoregressive exponential model for the scene reflectivity. Kuan considered a multiplicative speckle model and designed a linear filter based on the minimum mean-square error criterion, optimal when both the scene and the detected intensities are Gaussian distributed. The Lee filter was a particular case of the Kuan filter based on a linear approximation made for the multiplicative noise model. The Gamma filter was based on a Bayesian analysis of the image statistics where both intensity and speckle noise follow a Gamma distribution.

If the number of scattering points per resolution cell is large, a fully developed speckle pattern can be modeled as the magnitude of a complex Gaussian field with independent and identically distributed real and imaginary components (Goodman, 1976). It leads to the Rayleigh distribution as the amplitude distribution model. Despite the theoretical appeal and the analytical simplicity of the Rayleigh model, high-resolution SAR images of urban scenes and some natural scenes such as sea surface deviate from the Rayleigh distribution (Anastassopoulos, 1999). Various models have been proposed to accommodate this problem. The Weibull distribution used in modeling urban scenes and sea clutter and the k-distribution successfully modeled sea clutter. Both are a special case of Rayleigh distribution. The lognormal models suggested for radar image intensity based on image statistics alone.

Most SAR data are over-sampled by the SAR system to get pixel size less than the spatial resolution. Samples are then spatially correlated. Markov random fields (MRFs) have been used to model spatially correlated and signal-dependent phenomena for SAR speckled images. Texture involves the spatial distribution of intensity in a local region. It contains important information about the structural arrangement of surfaces and their relationship to their neighboring surfaces. The MRFs represent a local interaction of image structure and have been demonstrated to be quite effective for texture characterization (Manjunath and Chellappa, 1990).

The Point-Jacobian iterative *maximum a posteriori* (PJIMAP) method using a Bayesian model based on the lognormal distribution for image intensity and a Gibbs random field (GRF) for image texture has been proposed for despeckling the SAR images that are corrupted by multiplicative speckle noise (Lee, 2007). When the image intensity is logarithmically transformed, the speckle noise is approximately Gaussian additive noise, and it tends to a normal probability much faster than the intensity distribution (Arsenault and April, 1976). This paper extends the PJIMAP adaptively estimating the GRF coefficients at each iteration.

2. Bayesian Function for MAP Estimation

Since the effect of additive noise in SAR images is generally much less significant than that of speckle noise, SAR image model is often stated as

$$z_k \cong v_k \eta_k .$$

The use of a logarithmic transform converts the multiplicative model into an additive one:

$$\ln z_k = \ln v_k + \ln \eta_k .$$

Let $I_n = \{1,2,\cdots,n\}$ be the set of indices of pixels in the image. If η_k follows a log-normal distribution, $\ln \eta_k$ follows a Gaussian distribution, and if

$$Y = \{y_k = \ln z_k, k \in I_n\}, X = \{x_k = \ln v_k, k \in I_n\},$$

and σ_k^2 is a variance of $\ln \eta_k$, then

$$Y \sim N(X, \Sigma) \text{ where } \Sigma = diagonal\{\sigma_k^2, k \in I_n\}.$$

Image processes are assumed to combine the random fields associated with intensity and texture respectively. The objective measure for determining the optimal restoration of this "double compound stochastic" image process is based on Bayes' theorem. In the proposed algorithm, the MRF is used to quantify the spatial interaction probabilistically, that is, to provide a type of prior information on the image texture.

It is natural that neighboring pixels with more similar intensity levels have a higher probability of having the same level. Based on this idea, spatial interaction can be quantified for image texture processes based on a distance measure between neighboring pixels. Here, the energy function of the GRF is specified as a quadratic function of X, which defines the probability structure of the texture process:

$$E_p(X) = \sum_{i \in I_n} \sum_{(i,j) \in C_p} \alpha_{ij} (x_i - x_j)^2$$

where α_{ij} is a nonnegative coefficient vector which represents the "bonding strength" of the ith and the jth pixels, and C_p is the pair-clique system.

The log-likelihood function for the MAP estimation using the log-normal intensity model and the GRF texture model is:

$$\lambda PN \propto -(Y - X)'\Sigma^{-1}(Y - X) - X'\mathbf{B}X$$

where $\mathbf{B} = \{\beta_{ij}\}$ where

$$\beta_{ij} = \begin{cases} -\alpha_{ij} & \text{for } (i,j) \in C_p \\ \sum_{(i,j) \in C_p} \alpha_{ij} & \text{for } i = j \\ 0 & \text{otherwise} \end{cases}$$

is the bonding strength matrix.

3. Point-Jacobian Iteration MAP Estimation

Since the log-likelihood function is convex, the MAP estimate of X is obtained by taking the first derivative:

$$\Sigma^{-1}(Y - X) - \mathbf{B}X = 0 .$$

This equation can be solved by the point-Jacobian iteration (Varga, 1962). Decomposing the bonding strength matrix into a matrix with the diagonal elements and a matrix with the non-diagonal elements, the equation is rewritten as

$$
\begin{aligned}
X &= \mathbf{M}_d^{-1}\Sigma^{-1}Y - \mathbf{M}_d^{-1}\mathbf{B}_s X \\
\mathbf{M}_d &= diagonal\{\sigma_k^{-2} + \beta_{kk}, k \in I_n\}. \\
\mathbf{B}_s &= \{\beta_{ij} \mid \beta_{ii} = 0\}
\end{aligned}
$$

The noise-free intensity can be recovered iteratively: given an initial estimate of X, $\hat{X}^0$ at hth iteration

$$\hat{X}^h = \mathbf{M}_d^{-1}\Sigma^{-1}Y - \mathbf{M}_d^{-1}\mathbf{B}_s\hat{X}^{h-1},$$

equivalently

$$\hat{x}_i^h = \frac{1}{\sigma_i^{-2} + \beta_{ii}}\left(\sigma_i^{-2}y_i - \sum_{(i,j)\in C_p}\beta_{ij}\hat{x}_j^{h-1}\right), \quad \forall i \in I_n.$$

The iteration converges to a unique solution since $\gamma(\mathbf{M}_d^{-1}\mathbf{B}_s) < 1$ where $\gamma(\bullet)$ denotes the spectral radius (Cullen, 1972).

4. Adaptive Bonding Strength Coefficient Estimation

Various regions constituting an image can be characterized by textural components. The bonding strength coefficients are associated with local interaction between neighboring pixels and can provide some contextual information on the local region. It is important to choose the coefficients suitable for the analyzed image. Given a constant r, the Bayesian MAP estimation can be considered as an optimization problem:

$$\arg\min_X \left\{\sum_{i\in I_n}\sum_{(i,j)\in C_p}\alpha_{ij}(x_i - x_j)^2\right\} \text{ subject to}$$
$$\sigma_k^{-2}(y_k - x_k)^2 < r, \forall k \in I_n.$$

Since the objective function and the constraints are convex, the optimization is restated as

$$\arg\min_X \left\{\sum_{i\in I_n}\left[\sum_{(i,j)\in C_p}\alpha_{ij}(x_i - x_j)^2 + \lambda_i\left(\sigma_i^{-2}(y_i - x_i)^2 - r\right)\right]\right\}$$

where λ is a "Lagrangian coefficient." By taking $\{\alpha'_{ij} = \alpha_{ij} / \lambda_i\}$ instead of $\{\alpha_{ij}\}$. Suppose $\{\alpha_{ij}, j \in I_n \mid \sum_{j\in I_n}\alpha_{ij} = 1\}$ as the normalized coefficients associated with the relative strength of interaction between the individual types of pair-cliques at the ith pixel. These interaction coefficients represent a textural component for the local region corresponding to the ith pixel, and, adopting a Bayesian interpretation, $\phi_i = 1/\lambda_i$ is referred to as a parameter that represents the relative strength of prior beliefs compared to information on the observation.

If the normalized interaction coefficients are predetermined, the parameters $\{\phi_i\}$ and $\{\alpha_{ij}\}$ are then estimated from (Lee, 2007):

$$\hat{\phi}_i = \sqrt{\frac{r}{\sigma^2 \sum_{(i,j)\in C_p}\alpha_{ij}(y_i - y_j)^2}}, \forall i \in I_n$$

$$\hat{\alpha}_{ik} = \begin{cases} \dfrac{(y_i - y_k)^2}{\sum_{(i,j)\in C_p}(y_i - y_j)^2} & \text{for } (i,k) \in C_p \\ 0 & \text{otherwise} \end{cases}.$$

For the adaptive method, the parameters are estimated using X computed at each iteration instead of Y.

5. Experiments

For the experiment, 16-bit simulation images of multiplicative noise model were generated using various patterns. The speckle filters were applied to the simulation data of patterns. An example is iluustrated in Fig. 1. The simulated noisy observation image and the histogram of intensity values are shown in the first row of Fig. 1. The pattern used has 5 classes and with the noise-free intensities of 500, 1000, 1500, 2000, 2500. The number of pixels belonging to each class is displayed by the bar graph in Fig. 1. The observations are ranged in 0 and 12070 with a left-skew distribution. In the second and third rows, the results of despeckling using the PJIMA and the adaptive PJIMAP are illustrated.

6. Conclusion

The PJIMAP filters have been proposed for despeckling SAR imagery, which are an iterative approach to find MAP estimation of noise-free intensity. In the extensive experiments, the PJIMAPs demonstrated the capability to relax speckle noise and estimate noise-free intensity. The algorithms are established based on a multiplicative noise model using a log-normal distribution and a texture model using GRF.

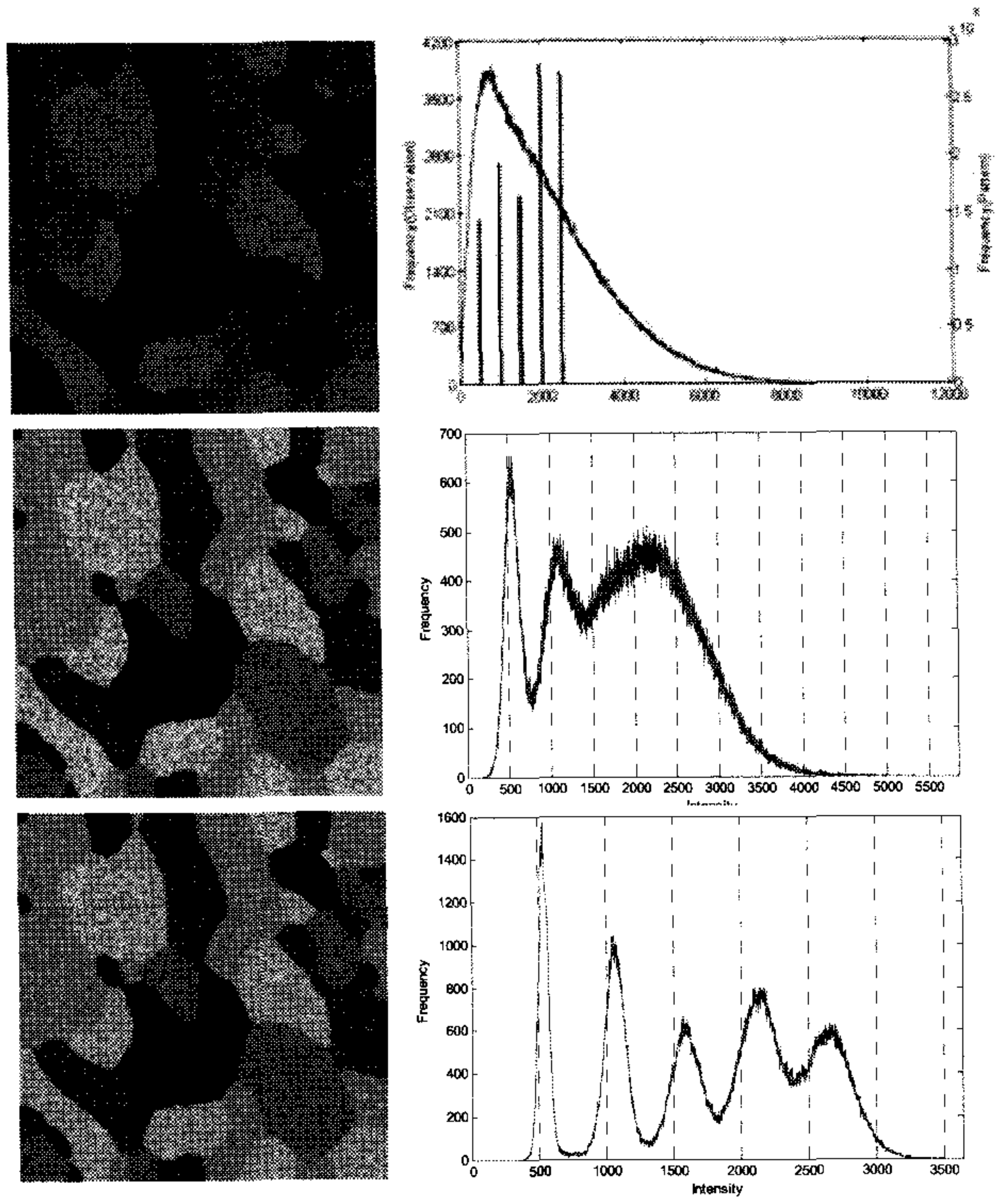

Fig. 1. Results of despeckling and histograms.

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