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Non-stationary speckle reduction in high resolution SAR images

Zhihuo Xu [a,b], Quan Shi [a], Yunjin Chen [c,*], Wensen Feng [d], Yeqin Shao [a], Ling Sun [e], Xinming Huang [f]

[a] *Radar & Image research group, School of Transportation, Nantong University, Nantong 226019, China*
[b] *Nantong Research Institute for Advanced Communication Technologies, Nantong 226001, China*
[c] *Institute for Computer Graphics and Vision, Graz University of Technology, Graz A-8010, Austria*
[d] *College of Computer Science & Software Engineering, Shenzhen University, Shenzhen, China*
[e] *Jiangsu Key Laboratory of ASCI Design, Nantong University, Nantong 226019, China*
[f] *Department of Electrical and Computer Engineering, Worcester Polytechnic Institute, Worcester, MA 01609, USA*

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A B S T R A C T

This paper attempts to address non-stationary speckle reduction in high-resolution synthetic aperture radar (HR-SAR) images, using a novel Bayesian approach. First, non-stationary speckle is defined. Second, an innovative log-normal mixture model (LogNMM) is proposed to model the underlying data; the data priors are represented by using Fields of Experts (FoE); and then the despeckling model is derived based on maximum a posteriori (MAP) method. The experimental results demonstrate that the proposal produces state-of-the-art despeckling performance on synthetic and real HR-SAR data, and prove that the speckle is non-stationary in the HR-SAR data of interest.

1. Introduction

Synthetic aperture radar (SAR) images are affected by the speckle noise, which is mainly due to the relative phase of individual scatters within a resolution cell [1–3]. The speckle is modeled as a kind of multiplicative noise [4,5]. The presence of such multiplicative noise makes automatic post-processing difficult [6,7], and therefore speckle reduction is a significant part of SAR image processing tasks. Many excellent filters have been developed to remove the speckle noise, such as the well-known Lee filter [4], maximum a posterior (MAP) based filters [5], wavelet based [8], Gaussian modeling [9], non-local means based filters [10–16], Markov random filed (MRF) based method [17], to name just a few. These excellent filters produce outstanding performances on despeckling SAR images in the case of the *fully developed speckle* noise.

The *fully developed speckle* is formalized as a random walk in the complex plane by Goodman [18]. The two key hypotheses of Goodman model for its statistical characterization are: 1) the number of independent scatterers per resolution cell is large enough and 2) the observed scene is homogeneous. So the central limit theorem can be applied to develop a circular complex circular Gaussian speckle model. However, when the resolution of SAR is close to the wavelength of sensors, it is more likely to have a limited number of scatterers inside a resolution cell. It means that the equivalent number of independent scatterers per resolution cell is so small that the distribution of speckle does not follow the Goodman model, as shown in Fig. 1. Especially, the issues become more outstanding for the images of SAR over heterogeneous areas [19], like urban areas, in which both non-stationary surfaces and man-made targets commonly appear.

As the techniques of *the fully developed speckle* filtering tend to be mature, this paper attempts to present a deeper question for a more complex model and spreading its use in *non-stationary speckle*. First, we make a definition of non-stationary speckle. Next, we present a log-normal mixture model (LogNMM) to fit the underlying data, due to that traditional statistical models cannot describe the high resolution SAR data well. To estimate the considered parameters of the LogNMM, we follow an iterative Expectation Maximization (EM) approach [20]. On the other hand, Fields of Experts (FoE) proposed by Roth and Black [21] has come into the spotlight. In practice, the FoE is a filter-based higher-order MRFs model, which has substantially improved the learning capability of the entire image priors. Following the concepts of the FoE, we adopt the existing prior model of SAR images in our previous work [17]. With the likelihood function via the LogNMM and the priors via the FoE, the posterior distribution is completely defined for despeckling. An efficient non-linear quasi-Newton method [22] is finally applied to explore the maximum of the posterior distribution.

* Corresponding author.
E-mail address: chenyunjin_nudt@hotmail.com (Y. Chen).

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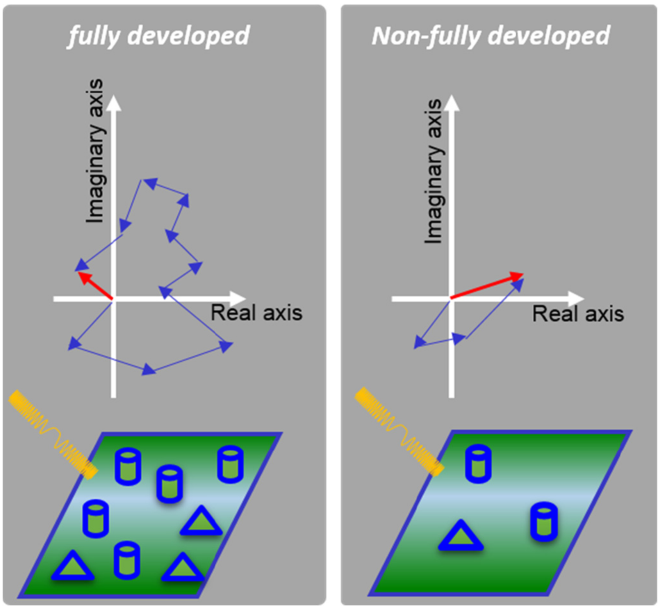

Fig. 1. Conceptual schematic of the fully developed and non-fully developed speckle.

This paper is organized as follows. Section 2 defines the non-stationary speckle. The despeckling algorithm is proposed in Section 3. The encouraging results are demonstrated in Section 4. Finally, conclusions are briefly drawn in section 5.

2. Stationary and non-stationary speckle

A weak form of stationary process is known as wide-sense stationary. Thanks to the wide-sense stationary, the stationary speckle process requires that both the first moment and auto-covariance do not vary with respect to (w.r.t.) the locations of the pixels within the SAR image. A two-dimensional speckle image can be converted into one dimensional vector as $\mathbf{S}(x)$ in column-wise order. So, $\mathbf{S}(x)$ which is stationary process has the following restrictions on its mean function

$$E\left[\mathbf{S}(x)\right] = m \tag{1}$$

and auto-correlation function

$$R_{\mathbf{S}}(x, x+\tau) = R_{\mathbf{S}}(\tau) \tag{2}$$

where m must be constant, and x denotes the location of pixels. The equation (2) implies that the autocorrelation function depends only on the difference between the location x and $x+\tau$. So it only needs to be indexed by one variable τ rather than two variables. When the speckle follows the above two properties, we called this type of speckle as stationary speckle. Otherwise, the stochastic characteristics of the speckle does not follow Eqs. (1)–(2), the speckle is defined to be non-stationary.

To better understand the differences between the stationary and non-stationary speckle, simulated stationary and non-stationary SAR images are shown in Fig. 2(b)–(c), respectively. The speckle images shown in the bottom of the Fig. 2(b)–(c) exhibit different features. In the case of stationary, the speckle trends to normal noise like. On the contrary, some artifacts can be clearly seen in the non-stationary speckle image. There are total 18 the auto-correlation results and mean values plotted in the Fig. 2(d) and Fig. 2(e), respectively. If the speckle is stationary process, the auto-correlation functions will be nearly same and overlapped together in the plots. As expected, the statistical properties of stationary fit well the equations (1)–(2). The mean values w.r.t. x are nearly constant, and the auto-correlation functions are nearly same. However, in the case of non-stationary, the mean values vary with respect to the locations of the pixels within the SAR image. Also the auto-correlation functions vary, like some bursts shown in the Fig. 2(e).

3. The proposed despeckling algorithm

3.1. Non-stationary speckle modeling

As mentioned above, traditional statistical models can not fit the high resolution SAR images well. Furthermore, the non-stationary speckle commonly appears in the heterogeneous areas. In [23], the log-normal distribution provides the most satisfying results in case of very heterogeneous areas. However, previous studies suggest that it is not perfect enough for characterizing the complex regions of the heterogeneous areas [23]. A recent study by Zhou et al. [24] demonstrated that the two-component log-normal distribution mixture model can better describe heterogeneous clutter regions, comparing with the single distributions. To model accurately the data, we thus present the LogNMM for the probability density function (pdf). Let A_j, $j = (1, 2, \cdots, N)$, denote an observation at the j-th pixel of a SAR amplitude image. The proposed LogNMM assumes that each observation A_j is modeled as independent and identically distributed samples drawn according to the following pdf

$$P_j(A_j \mid \theta) = \sum_{k=1}^{K} \pi_k p_k(A_j \mid \theta_k) \tag{3}$$

where $\Pi = \{\pi_k\}$, $k = (1, 2, \cdots, K)$ is a set of mixing proportions, which satisfies the constraints

$$0 \le \pi_k \le 1 \quad \text{and} \quad \sum_{k=1}^{K} \pi_k = 1 \tag{4}$$

and $p_k(\cdot \mid \theta_k)$ is called a component of the mixture, which is a log normal distribution function dependent on a vector θ_k of parameters. Each log normal distribution can be written as

$$p_k(A_j \mid \theta_k) = \frac{1}{A_j \sqrt{2\pi}\sigma_k} \exp\left(-\frac{(\log A_j - \mu_k)^2}{2\sigma_k^2}\right) \tag{5}$$

where $\theta_k = \{\mu_k, \sigma_k^2\}$, $k = (1, 2, \cdots, K)$. Note that the observation A_j in (3) is considered as statistically independent, the joint conditional density of the data set A_j, $j = (1, 2, \cdots, N)$ can be formulated as

$$P(\mathbf{A} \mid \Pi, \theta) = \prod_{j=1}^{N} P_j(A_j \mid \theta) = \prod_{j=1}^{N} \left[\sum_{k=1}^{K} \pi_k p_k(A_j \mid \theta_k)\right] \tag{6}$$

We augment the observation data $\mathbf{A} = (A_1, A_2, \cdots, A_N)$ by an unobservable matrix (called hidden data) $\mathbf{Z} = (z_{jk},\ j = 1, 2, \cdots, N,\ k = 1, 2, \cdots, K)$. The values z_{jk} are indicators, defined as

$$z_{jk} = \begin{cases} 1, & \text{observation } A_j \text{ comes from the distribution } p_k \\ 0, & \text{else} \end{cases} \tag{7}$$

Using the augmented data, the likelihood of complete data $X = (\mathbf{A}, \mathbf{Z})$ can be written as

$$P(X \mid \Pi, \theta) = \prod_{j=1}^{N} \prod_{k=1}^{K} \left(\pi_k p_k(A_j \mid \theta_k)\right)^{z_{jk}} \tag{8}$$

Given the observation A and the current parameter estimate $\theta^{(i)}$, the maximum of the expected value of the complete log-likelihood w.r.t. the distribution of the hidden variables can be

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