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This article [*J. Appl. Remote Sens.* **7**(1), 071598 (March 18, 2013)] contained several errors in equations and word choices, and significant words and phrases were omitted in several places.

On Page 5, the sentence beginning, "Prime examples of methods..." makes three references to "time-frequency" that should have read "space-frequency."

On Page 7, "dx" was dropped from Eqs. (6) and (7). Eq. (6) should have read:

$$PFA = \int_{\alpha}^{\infty} p(\mathbf{x}|\omega_B) \, dx.$$
 (6)

Eq. (7) should have read:

$$PD = \int_{\alpha}^{\infty} p(\boldsymbol{x}|\omega_T) \, dx.$$
(7)

On Page 11, in the sentence beginning, "Thus, CA-CFAR achieves..." the word "asymptomatically" should have been "asymptotically."

Numerous word choice and equation errors appeared in Sec. 5.2. The text has been corrected and reprinted below.

5.2 Understanding the Multiplicative SAR Data Models

In any target detection scheme that depends on parametric modeling (e.g., the popular CFARbased), the selection of an appropriate probability distribution to model the pixels in the SAR image (i.e., radar backscatter) is a must, because the thresholding operation in any such detector is dependent on the clutter distribution. In cases where the random scatterers in a resolution cell in the SAR image have sizes on the order of the wavelength of the radar signal, the total backscatter can be modeled as the sum of isolated returns in the cell.¹⁰¹ This invokes the CLT, wherein the *I* and *Q* components of the total complex-valued backscatter can naturally be assumed to be normally distributed. This implies that the total backscattered amplitude and phase can be modeled as Rayleigh and uniform distributions, respectively. Thus, the power in each resolution cell is modeled as an exponential distribution. Conversely, in high-resolution SAR, the above mentioned assumptions are violated, because the number of random scatters in a resolution cell is not large, and thus the CLT cannot apply. This renders the clutter non-normally distributed, which motivates the need for a suitable model.

The multiplicative model (also known as the compound model) for SAR image formation has been popularly used in the literature to model the clutter background. The model is based on the hypothesis that the SAR image is formed from the product of a backscatter and speckle random processes as

$$Z = X \times Y,\tag{33}$$

where X and Y are two independent random variables that represent the backscatter and speckle, respectively. X is often assumed to be a positive real variable, whereas Y is either complex or positive real, depending on whether the image is in the complex or intensity/magnitude domains. The product in Z models the observed SAR image.

Typically, for a single look (i.e., n = 1) SAR image, the complex speckle Y is characterized as bivariate normal density for complex imagery, which reduces to the exponential distribution in the power or intensity domain. Further, for multilook imagery (i.e., n > 1), the two-parameter gamma distribution $\Gamma(\alpha, \lambda)$ characterizes the speckle in the power domain, and this reduces to the square root gamma distribution $\sqrt{\Gamma(\alpha, \lambda)}$ in the magnitude domain. Depending on the type of the background clutter (i.e., homogeneous, heterogeneous, or extremely heterogeneous), and the pertinent sensor characteristics (i.e., operating conditions) such as frequency, polarization, and gazing angles, several different distributions are used in the literature to model the backscatter X. For each case, the manner in which X (and subsequently Z) manifests itself depends^{31,94} on whether the SAR image is single-look (i.e., n = 1) or multilook (i.e., n > 1).

First, for homogeneous regions and a single look SAR image, X is typically modeled as a constant that equals the average power in the homogeneous region (i.e., $C = 2\sigma_G^2$). Accordingly, the power-domain SAR image Z is modeled as exponential distributed:

$$Z \sim \exp\left(\frac{\alpha}{\lambda}\right). \tag{34}$$

Similarly, for a multilook SAR image (i.e., n > 1), $\alpha = n$, and $\lambda = n/(2\sigma_G^2)$. However, the power domain SAR image Z becomes gamma distributed:

$$Z \sim \Gamma\left(n, n\frac{\lambda}{\alpha}\right). \tag{35}$$

Second, for heterogeneous regions, the backscatter X is not modeled as a constant. Rather, it is modeled as a gamma distribution $\Gamma(\alpha, \lambda)$, or a square root gamma distribution $\Gamma^{1/2}(\alpha, \lambda)$, for power-domain and amplitude-domain SAR imagery, respectively. This yields the *K*-distribution model, $K(\alpha, \lambda, n)$ for any number of looks *n*.

Third, for extremely heterogeneous regions, the *G*-distribution⁹³ is typically used. Unlike the *K*-distribution, the *G*-distribution uses the square root of the generalized inverse Gaussian distribution to model the backscatter X for both homogeneous and heterogeneous backgrounds in the magnitude-domain:

$$X \sim \sqrt{N^{-1}(\alpha, \gamma, \lambda)}.$$
(36)

The speckle model is left unchanged as provided earlier. This model is the most generic, and the previous models are special cases of it. Indeed, $\sqrt{N^{-1}(\alpha, \gamma, \lambda)}$ leads to the following three special cases. First, the square root of the gamma distribution leads to the *K*-distribution. Second, the reciprocal of the square root of the gamma distribution leads to the *G*^o-distribution. Third, a constant leads to a scaled speckle (i.e., the homogeneous case), as explained in Eqs. (34) and (35), for single-look and multilook SAR imagery, respectively.

With the same number of free parameters (i.e., two parameters) as the *K*-distribution, the G^{o} -distribution can model extremely heterogeneous regions that the *K*-distribution cannot model. Finally, the G^{o} -distribution reduces to the beta-prime distribution, $\beta'(\alpha, \gamma)$, for single-look (i.e., n = 1) SAR imagery.³¹ The various multiplicative SAR models and the interrelation between them are summarized in Fig. 7.

All online versions of the article were corrected on 31 May 2013.